ASSESSING DETERRENCE IN THE FBI'S SAFE STREETS GANG INITIATIVE: A SOCIAL NETWORK APPROACH

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by

William Arthur Sharpe

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ABSTRACT OF DISSERTATION

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ABSTRACT

For nearly three decades, the Federal Bureau of Investigation has provided federal government resources to assist with local and state gang enforcement efforts through the Department of Justice's Safe Streets Violent Gang Initiative. During this time, the FBI has established the Safe Streets initiative as one of the most active gang enforcement efforts in the country—in a strategy where street gangs are portrayed as a form of criminal enterprise. This view of the groups animates an enforcement approach based on the FBI's Enterprise Theory of Investigation (ETI), which identifies and prosecutes gang leaders and highly involved gang members. Despite high levels of enforcement activity, and official claims linking these efforts to the dismantling of street gangs and reductions in gang violence, surprisingly little research has been conducted into the strategy. The current study adds to this limited body of research by examining Federal Bureau of Investigation efforts to combat street gang violence in the city of Lynn, Massachusetts. Through a social network-based approach, this research places this evaluation in the context of broader issues related to deterrence, punishment and the communication of risk. A diffusion of innovation framework is used to reconceptualize the principles of punishment to operate according to network principles of communication and peer influence within the groups targeted. In this framework, the effectiveness of sanctions and threats of punishment are accessed by individual perception and behavioral response. A longitudinal-based Stochastic Actor Oriented Model traces that response in accordance with the principles of specific and general deterrence among targeted and untargeted individuals. In this research, the general deterrence mechanism is enabled by the social ties between individual gang members, which serve to communicate information on punishment risk from targeted gang members to the untargeted. Analytically, social ties also function as the key measure in a diffusion of innovation model used for the first

time with a network of cooffenders. While the results of this research cannot be generalized because of its network approach, the study raises a number of important questions pertaining to the FBI's Safe Streets Violent Gang Initiative, and for future research. In particular, assumptions related to sanction severity in the FBI's approach to street gangs were not supported and the general deterrence mechanism linking punishment with communication, failed to impact the perception of risk in the desired direction. These findings highlight the need for more research into this very active and popular strategy. Additionally, diffusion models revealed a relationship between the observed patterns of ties between offenders and the communication process, which conditioned the transmission of risk information within the larger structure of the Lynn gang network. While limited to this network, this finding does raise a number of questions related to how deterrence-based messages may be communicated in gang and criminal networks.

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CHAPTER 1

INTRODUCTION

Throughout the 1990's and 2000's, the dramatic growth of street gangs alongside corresponding increases in firearm use and youth gang involvement coalesced to produce a significant spike in street violence that gripped the county (Weisel, 2002). Nationally, rates of homicide victimization for black males aged thirteen to seventeen tripled between 1984 and 1993, while the number of handgun homicides committed by juveniles quadrupled in a period in which non-firearm homicides declined by twenty percent (Blumstein, 2001; Cook and Laub, 1998:28). In the areas where street gangs were found "fluctuations in…murder and violent crime rates" also followed (Wood and Alleyne, 2010 102). This was especially the case in larger cities of the United States where 91% of law enforcement agencies serving populations between 100,000 and 249,999 and 96% of cities with populations over 250,000 reported gang related problems (Blumstein, 2001; Block and Block, 1993; Klein et al, 1991). In cities such as Chicago, escalations in retaliatory street violence and gang homicide resulted in a 33% murder rate increase in the city between 1987 and 1990 (Block and Block, 1993).

As the street gang became synonymous with problems of inner-city violence, political reactions led to calls for police to take a tougher stance and a policy shift towards deterrence-based gang responses was seen (Klein, 1993; Weisel, 2002). The first of these responses were reactionary efforts that consisted of police attempts to enhance the deterrent effects of enforcement through strategies that targeted gangs. In this type of response, known as targeted gang suppression, the police believed that by concentrating their enforcement activity, "the targets of suppression, the gang members and potential gang members [would] respond 'rationally' to suppression efforts [and]…weigh the consequences of gang activity, redress the balance between cost and benefit, and withdraw from gang activity" (Klein, 1995:160).

Beyond police-based approaches, the trend towards deterrence-bases gang response was informed by emerging criminological theory that brought focus to the offender and the criminal event. Theories such as rational choice, routine activities, and situational opportunity came to dominate crime policy by orienting police resources toward more focused interventions at an ecological/geographic level (Cohen and Felson, 1979; Sherman et al., 1989; Sherman and Weisburd, 1995; Clarke and Cornish 2001; Bowers et al., 2011). These theories enjoyed support from policy makers as they regarded the proximate causes of crime to be of prime importance in both defining the phenomena of crime and reducing its harm through criminal justice interventions (Bowers et al., 2011; Braga and Bond, 2008). Efforts predicated on the theories were bolstered by research suggesting that crime concentrates in space, regardless of what unit of analysis was employed, and with studies that supported the use of focused police resources on micro-places where local conditions contributing to crime could be addressed (Weisburd, 2008; Braga, 2007; Brantingham and Brantingham, 1999).

Additionally, Goldstein's (1990) problem oriented policing approach had preceded these perspectives in proposing a proactive police role in addressing enduring social problems contributing to crime; often through the incorporation of unconventional approaches outside of law enforcement (Kappeler and Gaines, 2015; Braga, et al., 2000). In the combination of proactive policing and place-based trends, a dramatic shift occurred in how police came to view their role in controlling crime, how they framed their response to community crime problems and how police effectiveness in controlling crime was accessed (Braga and Weisburd, 2012; Weisburd and Eck, 2004). When combined with deterrence theory, problem-oriented policing transformed traditional law enforcement tools such as patrol or arrest into a more effective form by focusing police resources against individuals, groups or crime hot spots (Weisburd and

Majmundar, 2018; Braga, 2008). In the street gang context, this crystalized in a deterrence strategy that focused sanctions and the threat of punishment against chronic offending gang members (Braga, et al., 2000).

In this mode of 'pulling levers' focused deterrence-based response, threats of punishment were communicated directly to gang offenders driving violence trends (Braga, 2008). When those threats failed, they were backed by the application of the strongest available sanctions in the sanctioning approach known as pulling levers (Braga, 2008). Through this approach, the removal of key gang offenders was intended to break cycles of gang violence towards a larger goal of gaining longer-term crime reductions (Braga, 2008). Recently, researchers have emphasized a focused deterrence component used to link crime-reductions with the successful communication of punishment threats among populations of targeted and untargeted gangs (Braga and Douglas, 2021; Braga, Apel, and Walsh, 2014).

In so doing, these efforts have deemphasized the role of sanctions in favor of the strategy's ability to generate effective deterrence-based messages spread by a communication mechanism that operates specifically in gang populations to reduce violence (Braga and Douglas, 2021; Braga, Apel, and Walsh, 2014). As a conceptual matter, this has moved the deterrence-based gang strategy towards a larger question involving the individual response to sanctions and threats of punishment, where decisions to commit crime are thought to be impacted. In the broader study of deterrence, this question is framed as the challenge of perception: a challenge marked by researcher difficulty in establishing the linkage between sanctions and their intended effects on decisions to commit crime (Apel, 2013; Paternoster, 2010).

At the outset, this is a challenge that has reflected difficulties in connecting punishment principles with methodologies that accurately reflect and measure centrally important processes

of communication and perception (Apel, 2013; Kubrin et al., 2009; Sarnecki, 2001). Current methodologies, such as surveys and to an extent, variable driven analyses have largely lacked the resilience to tap and measure the process of perception at the level where it has been proposed to operate (Apel, 2013; Smangs, 2010; Kubrin et al., 2009; Sarnecki, 2001). For example, Apel (2013) has cited how knowledge gaps persist in the linkage between sanctions, perception and behavioral response despite recent advancements in theory testing. Additionally, data restrictions have played a critical role in limiting the exploration of these processes specifically in the context of gang-based efforts and gang research (Papachristos, 2011).

In deterrence-based gang strategies, the challenge of perception has been either unrecognized in the case of targeted suppression efforts or hidden by dominant criminological frames in the case of focused deterrence. This study is framed by the question of perception as it focuses on the communication processes imbedded in a Federal Bureau of Investigation deterrence-based effort to combat street gang violence in the City of Lynn, Massachusetts. Two separate theoretical domains—deterrence theory and social network theory—are combined in this study to place communication at the heart of the effort to reduce and prevent gang violence through sanctions designed to impact the perceptions of risk in Lynn street gangs.

THE SAFE STREETS GANG INITIATIVE

The city of Lynn, situated along the Eastern coastline of the State of Massachusetts just ten miles north of Boston, is the urban center of Essex County.[1] As an urban center, the city has traditionally had higher rates of violent and property crime; however during the late 1990's and early 2000's, the emergence of nationally aligned street gangs and the proliferation of rival gangs

[1]According to the 2010 U.S. Census, Lynn was the fifth largest city in the Commonwealth of Massachusetts and the most populated city in Essex County with nearly 92,000 residents.

within the city served as the catalyst for waves of shootings and assaults motivated by group conflict and competition over local drug markets. As street gang violence continued to plague the city and local enforcement efforts failed to impact the problem, police officials would turn to the Department of Justice and the Federal Bureau of Investigation for assistance under a program known as the Safe Streets Violent Crime Initiative.

Established in 1992 under the Clinton administration, this initiative sought to facilitate a proactive federal role in local crime control efforts through one of three strategies administered by the Federal Bureau of Investigation; the National Strategy for Organized Crime and Drug Enterprise, the National Gang Strategy, and the National Violent Crime Strategy (Phillips, 2015; Federal Bureau of Investigation, 2018). Under the National Gang Strategy, investigative task forces consisting of FBI agents and local and state law enforcement officials work directly with state and federal prosecutors to target street gangs and reduce violence in areas where these groups are most prevalent; primarily in disadvantaged and mostly minority communities (Phillips, 2015; Federal Bureau of Investigation, 2018).

Over the past two decades, the strategy has become the FBI's most active anti-gang initiative in part because of a task force structure viewed as a force multiplier in efforts to control gangs and gang violence (Phillips, 2015; Weisel, 2002). In 2018, there were 169 active Safe Street Gang Task Forces operating in 55 of the FBI's 56 field offices throughout the United States—comprised of nearly 2,000 federal, state and local law enforcement officials (Federal Bureau of Investigation, 2018). Between 2000 and 2010, Safe Street Gang Task Force investigations resulted in 57,106 arrests, 12,169 state complaints, 29,273 federal indictments, and the conviction of 23,094 individuals (Federal Bureau of Investigation, 2011).

This level of enforcement is a reflection of 'Enterprise Theory of Investigation' (ETI); "a standard investigative model that the FBI employs in conducting investigations against major criminal organizations [which]…encourages a proactive attack on the structure of…[groups]" (McFeely, 2001). As implemented in gang investigations, ETI combines local investigators' knowledge of gang members and gang associates with short-term street level enforcement and consensual monitoring with informants "to identify, disrupt, and ultimately dismantle violent street gangs whose activities constitute criminal enterprises" (Weisel, 2002: 40).

The primary conduit for achieving these goals is a sanctioning strategy that applies federal enterprise statutes. These statutes include the Racketeer Influenced and Corrupt Organizations Act (RICO), Violent Crimes in Aid of Racketeering Activity (VICAR) and Continuing Criminal Enterprise (CCE) applied to local street gangs where "the prosecution is structured from the inception of the investigation…[based upon] a review of the available intelligence base to estimate the group's structure, membership and criminal activities" (Weisel, 2002:42) [2]

STREET GANGS AND GANG RESPONSE IN LYNN

In 2005, the Federal Bureau of Investigation established the North Shore Gang Task Force under the Safe Streets Violent Gang initiative to target street gangs in Lynn, Massachusetts

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[2] In 1970, the United States Congress passed the RICO act to apply to organized Mafia groups, but under the seminal case of U.S. vs. Turkette, 452 U.S. 576 (1981) the Court held that street gangs engaged in enterprise (a requirement of the RICO statute) could be prosecuted even if all of the gang members were not involved (Agnifilo, Bliss and Riordan, 2006). An "enterprise" is defined by statute as including any individual, partnership, corporation, association, or other legal entity, and any union or group of individuals associated in fact although not a legal entity (18 U.S.C.A. § 1961(4)). The application of "RICO provides a federal avenue to target gangs within any jurisdiction of the United States", and directly addresses a limitation arising from a lack of state statutes dealing specifically with street gangs (Woods, 2011: 304). VICAR is a statute that punishes several categories of violent offenses committed in furtherance of a RICO organization and its' activities, which the court recently held in Boyle v. United States, 129 § 2237 (2009) applies to street gangs even if they lack an organizational hierarchy or a membership who have fixed and defined roles (Woods, 2011). The Continuing Criminal Enterprise Act, 13 U.S.C.A. § 848, is a sentencing enhancement statute that conveys severe penalties, including potential life sentences for large scale narcotic trafficking offenses committed as part of criminal enterprise.

thought responsible for violence. In terms of their history, street gangs in Lynn have been traced to the collapse of the Khmer Rouge in 1979 when more than 150,000 Cambodian refugees were resettled in the United States (Smith-Hefner, 1999). In Massachusetts, the cities of Lynn, Lowell, and Revere were designated as primary resettlement zones for refugees. With continued migration influenced by progressive social welfare policies and employment opportunities during the 1980's, the cities of Lynn, Lowell and Revere became home to heavily concentrated Cambodian communities (Tang, 2010; Smith-Hefner, 1999). According to 2000 census data, the City of Lynn featured the fastest growing Cambodian population amongst all cities and towns in the State of Massachusetts (Tang, 2010).

In the early 1990's, Cambodian youth groups began coming to the attention of the police for delinquent offenses such as vandalism, petty theft and truancy. By the end of the decade, the groups had become more street oriented and their crimes more serious in simple and aggravated forms of assault. This evolution of street gang violence in Lynn coincided with the introduction of nationally aligned and recognized street gangs. According to law enforcement officials, these street gangs—the Gangsta Disciples, Latin Kings, Tiny Rascal Gang, and Bloods and Crips—were attracted to Lynn because of the profit potential from the city's narcotics market. The competition for alignment and allegiance with these national groups produced different gang "sets" that would come to determine and influence patterns of group conflict that would play out on the streets of the city.

The most powerful to emerge through this process were the Deuce Boyz and Soldiers, who along with the Latin Kings formed the largest allegiance of Bloods under the referent "People Nation" title. Under the rubric of "Folk Nation", the Avenue King Crips—the most powerful Crip gang in Lynn—aligned with other gangs such as the Asian Street Walkers, the

Khmer Crips, Asian Boyz and Tiny Rascal Gang.[3] The escalation of violence in Lynn was linked to the murder of senior Blood gang member, Savon Prom, by the then leader of the Avenue King Crips (AKC), Derek Wright in the summer of 2000. This murder, according to investigators, served as a springboard for the establishment of more rigid gang affiliation lines as well as the basis for waves of retaliatory violence. The Prom murder, intended to establish the Avenue King Crips as the most powerful gang in the city, actually served to create a power vacuum after the leader of the AKC was convicted and sentenced for the murder. This sent into motion a process whereby new leadership used violence as a way to establish their bona fides against the Blood gang sets in the city.

The Crips and Bloods would become embroiled in an internecine state of war with the streets of Lynn serving as its battlefield. From the period between 2006 and 2008, 30 identified gang members were shot and 7 gang members were arrested in connection with those incidents.[4] In the first North Shore Gang Task Force intervention titled 'Deuces Wild', police intended to target key players orchestrating city violence, but over the course of the operation, officials found that gang involvement in Lynn's narcotic markets had grown and that illegal firearm sales had become part of the enterprise activities of city street gangs. This growth ironically gave rise to an incident leading to the sudden halt of the investigation in May of 2007 as an FBI informant was nearly killed during an attempted purchase of illegal firearms.

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[3] According to the National Gang Information Center, Folk Nation is not a gang, but maintains a charter and code of conduct derived from an "all for one and for all" philosophy. Folk nation is comprised of different ethnicities and its presence in the United States military has been observed more recently. Both Folk and People Nations originated in Chicago and have presence now throughout the country.

[4] These statistics derive from an internal tracking spreadsheet maintained by the Lynn Police Gang Unit on gang related violence. While validity concerns with official data are always present when it comes to how gang members are identified, the validity of gang membership and the classification of gang related violence were evidenced in this data by the number of individuals who were either shot multiple times or were both victims and suspects in gun incidents.

Insights into the structure of the gangs and their enterprise activities as well as the identities of key figures within the gangs were just beginning to blossom. A limited number of gang members—seventeen in total—were charged and prosecuted for mostly drug and weapon sale activity, and although the effort was initially regarded by law enforcement as a success owing to a year of relative peace between gangs, the operation would leave a void in the drug and gun markets (O'Brien, 2010).

This void provided an opportunity for untargeted gangs to expand their enterprise interests. According to FBI Special Agent Jeffrey Wood, the expansion of criminal activities by gang leaders, members and associates re-established violence as a primary means by which gangs could establish their foothold in the drug markets of Lynn.[5] For example, during one weekend in June of 2008, seven shootings that resulted in four gunshot victims and one death, was followed by the retaliatory stabbing of a rival gang member. In June of 2009, eight separate shootings took place with four gang members shot, including two teenage males. In retaliation, a gang member's residence was firebombed and two further shootings took place. In July of the same year while frightened bystanders dove for cover, two rival gang members squared off on a public beach in broad daylight firing bullets at each other until their guns were empty of ammunition.

In terms of the FBI's approach to this violence, successes derived from the FBI's Enterprise Theory of Investigation in cultivating informants during the 2006 Deuces Wild transformed an initial short-term intervention into a multi-year investigation that spanned gangs, leaders, senior members and associates across the city from 2006 to 2013. This expansion was facilitated through the larger set alliances previously described and with the increased

[5] Affidavit of S.A. Jeffrey Wood (2010:3).

involvement of gangs in city drug and gun markets. The second FBI effort in 2009, Operation Melting Pot, followed as the most encompassing attempt to target and dismantle violent street gangs in the city. Cooperating witnesses were used in the operation "to make controlled buys of narcotics and firearms from leaders, members, and significant associates of the Bloods, Deuce Boyz/Soldiers, Latin Kings and Latin Gangster Disciples" (affidavit of SA Jeffrey Wood: 16). From these purchases, a large number of individuals were identified and targeted, and at the conclusion of Melting Pot in November of 2010, sixty-one gang leaders, intermediate members and associates were arrested and charged with a litany of gun and drug trafficking charges. In addition to those charged in the operation, large quantities of powdered cocaine, crack cocaine, marijuana, and nearly $120,000 were seized along with 45 illegal firearms.

At a press conference announcing the arrests, officials would claim that:

> Since the inception of the FBI led North Shore Gang Task Force, it has generated remarkable results. Today is clear evidence of that success. Neighborhoods in Lynn and Lowell are much safer today than they were yesterday. No longer will senseless violence from a decade-long feud keep the community hostage. This investigation, previous ones, and those ongoing, reflect our collective dedication to deterring gang activity. Though our resolve is apparent in the number of arrests made by the task force over the last number of years --- in Operation Melting Pot alone the task force made nearly 60 arrests --- we will continue to actively identify individuals throughout the Commonwealth involved in unlawful gang activity. (United States Attorney, District of Massachusetts, 2010)

Two additional operations would follow Melting Pot: Operation Melting Pot II in 2011, and the two-phased Operation Whiplash in late 2012 and early 2013. Across all operations, the North Shore Gang Task Force would arrest 158 individuals with 69 of these individuals charged and indicted for violating federal enterprise statutes.

THE CURRENT STUDY

In the current study, the effectiveness claims of the FBI are accessed in an approach that combines the lens of deterrence with social network theory to develop a deeper and more

nuanced understanding of communication and peer influence processes. Such an approach has been facilitated by a unique data set that combines information on social relations and individual attributes in order to access the analytic theme that has dominated discourse on deterrence theory—the question of how sanctions precisely impact individual perception of risk (Paternoster, 2010). This type of ‘network’ data has been used across the social sciences, and it holds potential to examine “various analytical themes that are at the center of the main theories of crime” (Morselli, 2009:4). In the current research, the street gang is placed at the center of a new approach to deterrence theory testing in line with calls for more social network-based studies of street gangs (Sierra-Arévalo and Papachristos, 2015).

In this study of gangs and deterrence, a social network framework connects communication of risk and peer influence with the individual’s punishment response to the sustained enforcement activities in Lynn by the North Shore Gang Task Force. This is less a departure from the principles of deterrence theory and more a reconceptualization of a deterrence process that embraces the “position that crime is a social activity, and there are systemic interdependencies among actors” where insights may be sought in the networks of the street gang (Faust and Tita, 2019).

Chapter 2 considers how deterrence theory and the measurement of its’ principles have evolved. This chapter tracks this evolution from the origins of deterrence as a theory of punishment to one in which conceptual complexities are matched only by difficulties in demonstrating the effectiveness of punishment in altering behavior. The chapter then transitions into the application of deterrence theory in the context of street gangs. Definitional issues are discussed in order to specify the types of groups that have been targeted in deterrence-based approaches. This is followed by a discussion on the ways in which principles of punishment

have been conceptualized and applied to street gangs in two principle strategies: targeted and focused deterrence. In the street gang context, the recent evolution of deterrence-based principles has implicated the need to identify processes of communication and perception, a need for which social network-based approaches are ideally suited.

Chapter 2 then transitions the discussion towards social network theory where the reader is introduced to the science of social networks and the dependency assumptions that dominate the study of social phenomenon in network-based approaches. This in turn lays the foundation for the networked theory of deterrence presented in the chapter. This networked theory consists of three conceptual components: behavioral dependency, communication, and peer influence derived from connections between individuals. These components are described in this chapter within a diffusion of intervention framework that compliments principles of deterrence and processes of communication in the anti-gang strategy.

Chapter 3 moves to the analytic approach of the study, which is based on the Stochastic Actor-Oriented Model. This chapter orients the reader to the way in which network assumptions of dependency are incorporated at the mathematical level in order to model the dynamic processes of social selection, social influence and behavior in networks. The Simultaneous Diffusion of an Innovation and Evolution of a Dynamic Network model, the model used in this research, is then discussed. This chapter also frames the diffusion of innovation analysis assessing the impact of the FBI's Safe Streets Gang Strategy on the offending behaviors of targeted and untargeted gang members in Lynn. Study data and measures are then presented at the end of Chapter 3.

Chapter 4 presents descriptive measures on both study participants and the social network examined. This is followed by the analytic results from the study's diffusion of innovation

models. The results of these models spurn additional discussions in the chapter related to punishment certainty, and the interaction between offender network ties and the flow of information within the larger relational network of street gangs in Lynn.

Lastly, Chapter 5 presents theoretical and policy conclusions that can be drawn from this study including major findings related to the severity of punishment, the role of race in the Lynn gang efforts, and the dependency between cooffending ties and communication in the larger gang network. Also considered are the limitations of the current research as well as the potential for the study's social network methods to supplement the body of research generated in connection with the study of deterrence in the street gang context.

CHAPTER 2

THEORETICAL CONSIDERATIONS

In this chapter, we consider the evolution of deterrence theory from its advent as a reformatory justice effort initiated during the Enlightenment to its present policy-focused form where theoretical and measurement issues have centered on the challenge of perception. In this movement is a deterrence theory that has heavily influenced and shaped the criminal justice systems of most Western democracies where it remains one of the most enduring and appealing theoretical perspectives regarding crime (Blumstein, Cohen and Nagin, 1977; Kahan, 1997). This appeal connects to a theory that strikes a common chord with notions of retribution and revenge for those who violate individual sanctity and broader conduct norms, and with an easily understood premise that individual decisions and behaviors are shaped by available incentives and disincentives (Nagin, 2013; Tonry, 2008). It is in this simple premise where the evolutions of punishment principles have taken place, and where the challenge for deterrence-based gang strategies ultimately connect (Loughran, et al., 2011).

CLASSICAL DETERRENCE

Deterrence theory has its roots in the pre-Enlightenment, during a time when existing justice systems were criticized for their procedural unfairness and for the imposition of overly cruel and harsh punishments (Einstadter and Henry, 2006; Paternoster, 2010). The main philosophers of this period, Montesquieu, Voltaire, Beccaria and Bentham, regarded crime as an individual choice reflective of a decision-making process—a process guided by the costs versus the benefits of committing an act.

Bentham (1988) believed that because humans were hedonistic, the cost/benefit decision was strongly influenced by the desire to maximize pleasure at the expense of pain. This pursuit

of pleasure was viewed as antithetical to organized societies, and required individuals to surrender certain inherent rights in order to gain the protection of the state as part of a social contract (Beccaria, 1764). The desire to control individual drives engendered the establishment of normative laws on behavior and the provision of penalties for violations, thereby preventing a state of "original chaos" that would serve to undermine society (Einstadter and Henry, 2006, citing Beccaria, 1764a: 12).

The theory of deterrence is effectively a theory of punishment that links the decision-making process to the imposition of formal penalties matched to the harm caused society (Beccaria, 1764). Punishment, as the conduit to deterrence, serves first to raise the costs associated with crime through the individual's loss of freedom and the pains associated with imprisonment, while secondly, the punishment of the individual is intended to inhibit other society members from similarly committing offenses (Nagin, 2008; Bentham, 1988; Beccaria, 1764). This conceptualization of punishment and its effects ultimately shapes and defines classical deterrence theory and the distinctions made between specific and general deterrence, respectively (Paternoster, 2010; Zimring and Hawkings, 1968).

While deterrence theory endured a period of dormancy in terms of academic study—especially in the early 20th Century when American criminologists began to call into question deterministic assumptions regarding crime and free will—the theory attracted renewed interest from researchers in a variety of disciplines throughout the 1960's (Cook, 1980; Nagin, 1998). These researchers examined the viability of the theory's central concepts, which had not been subjected to rigorous empirical research (Silberman, 1976; Blumstein, Cohen and Nagin, 1978). This would produce a neo-classical deterrence theory where refinements in principles derived from the influence of economic and psychological research (Cook, 1980; Paternoster, 2010).

One of the most transformative was Becker (1968), an economist interested in understanding how many resources and how much punishment should be used to enforce different laws. Becker's (1968) inclusion of Expected Utility Theory and its development of the rationale offender were his main contributions to deterrence theory (Cook, 1980). "Expected Utility Theory (EUT) states that the decision maker (DM) chooses between risky or uncertain prospects by comparing their expected utility values, i.e., the weighted sums obtained by adding the utility values of outcomes multiplied by their respective probabilities" (Mongin, 1997: 342). In the crime context, Expected Utility Theory altered the basic tenets of Bentham's (1988) pleasure and pain concept by recognizing "that a person commits an offense if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities" (Becker, 1968:9). [6]

Becker (1968:17) believed that offenders were capable of making utility assessments through a rational weighting process, whereby an offense became a function of the probability of conviction, the punishment imposed at conviction and a variety of other variables such as the income available to the individual from both legal and illegal activities and the individual's willingness to commit an offense. On this last variable, willingness to commit an offense, Becker (1968) posited that individuals with lower incomes would prefer the risk of offending to other alternatives, especially provided that,

> "In equilibrium, the real incomes of persons in risky activities are, at the margin, relatively high or low as persons are generally risk avoiders or preferers. If offenders were risk preferers, this implies that the real income of offenders would be lower, at the margin, then the incomes they could receive in less risky legal activities, and conversely if they were risk avoiders" (p.12).

[6] Cook (1980) credits Becker (1968) with improving upon Bentham's original conception of pleasure and pain and hence, heavily influencing the direction of deterrence and policy research. The expected utility proposition subsequently influenced the development of criminological theories such as Rational Choice and Situational Opportunity theories, which portend the ability to impact crime decisions through the manipulation of the local environment (Cullen and Agnew, 2013; Piquero et al., 2011; Wilson et al., 2017).

The concept of risk avoider and risk preferer were key to Becker's conclusion that "some persons become 'criminals'…not because their basic motivation differs from that of other persons, but because their benefits and costs differ" (Becker, 1968: 9).[7] As a result, Becker (1968) argued that policy could be tailored to alter the utility equation for those on the margins. In citing examples such as murder, rape, and burglary, he spotlighted how crimes with the highest percentage of conviction and the strongest penalty response presented the most risk for individuals and the least expected utility, thus their incidences were comparatively less to other crimes for which expected utility was greater (Becker, 1968).

NEO-CLASSICAL DETERRENCE

Becker's (1968) joining of EUT and the rational offender crystalized into the marginal deterrence hypothesis, which states that "an increase in the probability or severity of punishment for a particular type of crime, or both, will reduce the rate at which that crime is committed, other things being equal" (Cook, 1980: 216). As developed over time and reflected in sanctioning policy and policing strategies, the marginal deterrence hypothesis proposes that changes can be brought about in pre-existing deterrence levels through formal policies and practices that increase the severity or certainty of punishment (Nagin, 1998; Durlauf and Nagin, 2011). In contemporary terms, direct punishment or rather, specific deterrence, is linked with the incapacitative effect of incarceration. At the same time, general deterrence has been refined to include the processes by which individuals contemplating offenses are deterred through the probability of being caught (certainty), the punishment associated with being caught (severity) or the immediacy of punishment (swiftness or celerity) (Nagin, 1998; Piquero et al., 2011).

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[7] Becker's (1968) conclusions led deterrence theory on a non-sociological path as it represented a rejection of dominant criminological theories of the time (strain, social learning, labeling) and encouraged a focus on the role of formal authority in controlling crime (Cook, 1980).

Alongside these refinements, psychological perspectives on punishment altered the original general deterrence mechanism (Paternoster, 2010). Here a conceptual shortcoming was identified in the inference that society members are aware of the potential penalties for law violations, and that this awareness is distributed equally among a society's population through the general deterrence mechanism (Bell, 1955). A legal scholar by training, Bell (1955) theorized that the relationship between the existence of penalties and their effects were not predicated on the actual imposition of sanctions, but rather would be dependent on the awareness of individuals to the potential penalties. In a process that would determine the general effectiveness of law in deterring behavior, awareness is a function of not only individual knowledge of penalties proscribed in statutory law, but also the individuals' assessment of penalties imposed if the law were violated (Bell, 1955).

In a similar vein, Geerken and Gove (1975:499) likened deterrence to a system of communication intended to inform a potential offender that the probability of being detected, convicted and punished is high and that the severity of punishment is sufficient to offset any gains from a criminal act. This system, conceptualized as the "collection of elements", contributes to deterrence in elements distinguished between informal and formal systems. Informal systems operate through interpersonal communications and involve interpersonal sanctions. Among these, are the loss of support or respect from others whose opinions or influence matters to the individual (Geerken and Gove, 1975: 500). Formal systems rely upon "legally recognized enforcement agents of predefined negative sanctions for violation of explicitly codified rules" (Geerken and Gove, 1975: 501).

In order to properly test the theory, Geerken and Gove (1975:489) proposed that researchers identify "how actual risk relates to perceived risk and how perceived risk relates to

behavior", which requires at the conceptual level, an appreciation of the difference between the objective and subjective properties of punishment and how threat communication bridges that gap. This perspective has been credited with changing deterrence theory from a macro-level theory of crime based in formal authority and law to a micro-level theory rooted in a "social psychological theory of threat communication" (Paternoster, 2010: 780). In this transformation, two fundamental distinctions between punishment and risk have arisen in the context of the marginal deterrence hypothesis (Paternoster, 2010; Tittle and Rowe, 1973; Williams, et al., 1980). As reflected in Figure 1, existing levels of objective risk are intended to be elevated through sanction policy change where commensurate increases in perception risk are expected, thereby reducing individual decisions favorable to committing an offense (Paternoster, 2010; Silberman, 1976; Geerken and Gove, 1975). The ability of formal sanctions to generate acuity and positive risk response to an increase in the certainty, celerity and severity of punishment amongst sanctioned individuals and unsanctioned populations lies at the heart of the marginal deterrence hypothesis (Paternoster et al., 1982; Cook, 1980).

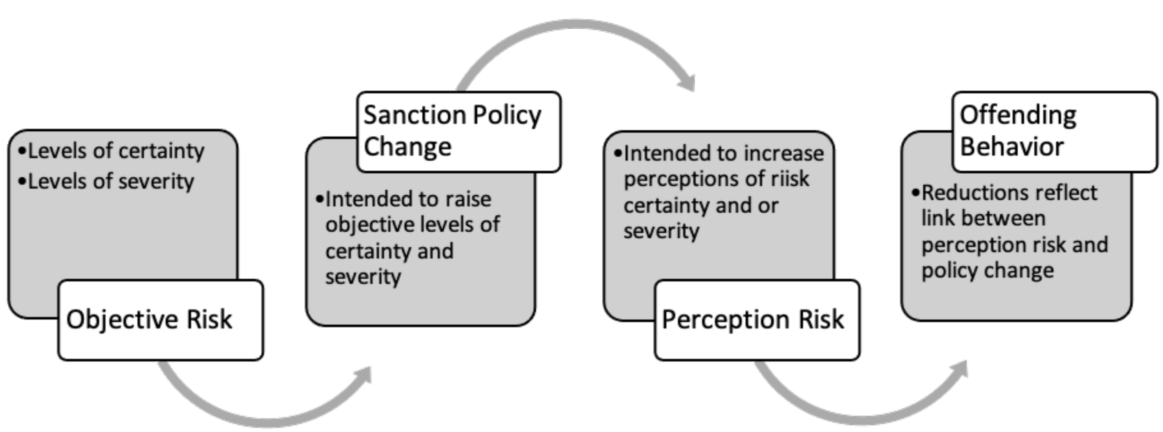

Figure 1: Marginal Deterrence as a System of Communication

This hypothesis proved to be a clarion call for policy makers seeking to address perceptions of a crime problem in America during the 1970's (Tonry, 2008; Williams, et al., 1980). All manner of tough on crime arguments followed leading to calls for the death penalty to be reinstated and the creation of more punitive approaches to offenders such as three-strike laws (Blumstein, Cohen, and Nagin, 1978). The marginal deterrence question—whether certain or severe punishments were effective in reducing crime—was a key area investigated by the Panel on Research on Deterrence and Incapacitation (PRDI) (Blumstein, Cohen, and Nagin, 1978). The panel also accessed whether there was a measurable, overall deterrent and incapacitative effect of sanctions on crime rates (Tonry, 2008; Nagin; 1998; Cook, 1980; Blumstein, Cohen and Nagin, 1978).

With respect to this latter question—of whether the criminal justice system as a whole had an effect on crime rates—Blumstein, Cohen and Nagin (1978), confirmed that it indeed did have an effect. This was referred to as an absolute deterrence effect, which is induced from having a system of penalties with an apparatus to regulate their use, thereby preventing most members of society from acting upon their impulses (Nagin, 1998). While this finding may be of interest, Cook (1980:214) noted at the time:

> "The everyday debates in the criminal justice policy arena are not, of course, concerned with whether to stop punishing criminals entirely, but rather with questions of degree: how many tax dollars should be devoted to apprehending and punishing criminals, how severe a punishment is appropriate for each crime type, and so forth. The evaluation of these issues hinges in part on our assessment of the marginal deterrent effects of changes in the certainty and severity of punishments, a more problematic issue than assessing the overall deterrent effect of current threat levels…Estimating the magnitudes of marginal deterrent effects stemming from various criminal justice system activities is the ultimate task facing scholars in this area".

The first studies examining marginality relied on aggregate crime data—incarceration and crime rates—from which the effect of a particular incarceration or law enforcement policy was extrapolated, while later studies used survey methodologies to explore the relationship between legal sanctions, perception and self-reported illegal acts (Paternoster et al., 1982).[8] Aggregate data research was implicitly oriented towards the severity component of deterrence and in these studies, rising incarceration rates in the face of declining crime rates were seen as positive indicators for the deterrent effect of "tough on crime" measures (Sorg et al., 2012).

Methodologically, aggregate deterrence research used incarceration rates as an independent, rather than policy outcome variable, which was criticized as operating outside the basic tenets of a theory that functions according to the incapacitation of the individual and with the prevention of future offenses. As Durlauf and Nagin (2011:18) described this problem:

> "Absent a deterrent effect of policy, crimes averted by incapacitation necessarily require the incarceration of the individuals who otherwise would be committing crimes outside the prison walls. However, if deterrent effects are present, then heightened sanction risks, when perceived as credible, can result in both lower crime rates and lower imprisonment rates. Again, the intuition is straightforward; deterred crimes mean that no one can be punished for them".

Positioned this way, aggregate data approaches had difficulties in making cause and effect arguments as "crime rates affect imprisonment rates even as imprisonment rates might be affecting crime rates" (Durlauf and Nagin, 2011:25). Consequently, this approach failed to produce reliable findings supportive of marginal changes in crime policy (Sorg, et al., 2012).

In survey-based research, findings supported the deterrent effects of certainty risk, but not the effects of risk severity (Stafford and Warr, 1993; Paternoster et al., 1982). While

[8] A third method, aggregate time-series design is discussed below in reference to deterrence-based gang strategies (Nagin, 1998).

contradicting the previous findings, early studies were criticized for their reliance on juvenile populations sampled from schools—populations not likely affected by marginal policy changes in crime policy (Nagin, 1998). In subsequent research, a focus on the "perceptions of formal, legal sanctions in response to criminal behavior, specifically encompassing arrest, prosecution, and incarceration" coupled to the surveys of adult populations (Apel 2013:68). These studies most often found that individuals overestimated certainty of risk while underestimating the severity risk of punishment (Jacobs, 2010). Additionally, a wide range of null, positive and negative effects were found in hypothetical scenarios manipulating objective levels of punishment (Apel, 2013; Piquero, et al., 2011; Paternoster, 2010).

ISSUES OF PERCEPTION IN DETERRENCE RESEARCH

This variability led to a larger question of "not whether sanctions deterred, but under what conditions or what kinds of persons [were] deterred, and when and for whom [sanctions] made things worse or were simply irrelevant" (Piquero et al., 2011:336). This question has led to conceptual refinements and the application of decision-making models, which focus on the factors that condition risk perception, and that produce variability in individual response (Pogarsky, 2014; Apel, 2013; Jacobs, 2010). Rational choice theory, which provided a unifying decision-making framework for examining situational and environmental factors in place-based efforts, is one such refinement (Jacobs, 2010; Clark and Cornish, 1985). In place-based efforts, rational choice theory led to the identification of situational and environmental factors underlying the criminal careers of offenders and the criminal event itself with the goal of manipulating those factors to prevent crime (Clark and Cornish, 1985). It's extension to deterrence theory serves a similar function. For instance, the incorporation of rational choice theory with Becker's (1968) expected utility model has facilitated the concept of *deterrability*, which connects the "perceptual process by which would-be offenders calculate risks and rewards

prior to offending…to the offender's capacity or willingness to perform [the] calculation (Jacobs, 2010: 417).

Bayesian theory has also been incorporated with deterrability to motivate a rational choice view of offenders as they update their risk perception in light of new offending experiences and new information received on punishment (Pogarsky et al., 2017; Kreager and Matsueda, 2014; Anwar and Loughran, 2011).[9] These models attempt to formalize the linkage between objective risk and sources of variation in risk response (Kreager and Matsueda, 2014). In this regard, models have accessed the effects of individual characteristics such as ambiguity, self-control, impulsivity and intelligence on observed differences in the updating of risk (Wilson, et al., 2017; Thomas, et al., 2013; Loughran, et al., 2011).[10] They have also facilitated the issue of deterrability through more global frames such as the concepts of offender 'discounting' and 'resetting' (Anwar and Loughran, 2011). Discounting is a phenomenon that involves offenders who negate longer-term consequences in favor of shorter terms gains while resetting involves offenders who discount risk based on their previous experiences with not being caught or punished (Thomas et al., 2013; Pogarsky and Piquero, 2003; Wilson and Hernstein; 1995).

While these models have been promising, their results have been mixed in validating the sources of perception risk variation. In one study, support for the global process of resetting was

[9] Bayesian theory traces to the field of psychology, but as applied in deterrence research, models provide "a mechanism for risk communication consistent with rational choice theory" (Kreager and Matsueda, 2014:117). These models have been used to make previous proposals tractable by accounting for second hand information on risk. For instance, Stafford and Warr (1993) proposed that information on punishment risk was sourced from direct experience with punishment and punishment avoidance as well as indirect experience derived from others' experiences with punishment and its avoidance (Nagin, 1998; Kreager and Matsueda, 2014). In this way, these models are proposed to be a more realistic interpretation of risk perception processes (Anwar and Loughran, 2011)
[10] Under Bayesian modeling, individuals "begin their criminal careers unsure about what their actual [risk] arrest will be…They thus form a subjective belief about this probability, termed their prior perception" (Anwar and Loughran, 2011: 67). As individuals commit offenses and access their chances of being arrested or sentenced, or as they receive information concerning punishment risk, they update perception in a more informed 'posterior' risk belief (Anwar and Loughran, 2011).

indicated by individuals who reported committing less offenses and higher rates of updating risk than more experienced offenders (Anwar and Loughran, 2011). However, when Thomas, et al., (2013) included individual measures on impulsivity and intelligence, increased risk perception was found amongst serious offenders, which was most pronounced amongst offenders with lower intelligence and higher scores on impulsivity. Bayesian models have also been criticized for their modeling assumptions and measurement of risk, and their view of decision-making under rational choice theory (Pogarsky, et al., 2017).

The notion of the rational offender is controversial because it presents a decision making-model that infers a uniform response to the cost and benefit parameters of the expected utility model (Pogarsky et al., 2017). This critique sources from a heuristics and biases program and a discipline of behavioral economics that focuses specifically on the nature of decision-making (Pogarsky, et al., 2017). Questions of how decisions are made have been advanced by logic, statistics or heuristics; rules of logic and statistics dominate rational decision-making models while heuristics links to the dimension of irrationality in the decision-making process (Gigerenzer and Gaissmaier, 2011). Consequently, in the heuristics and biases program, "a heuristic is a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods" (Gigerenzer and Gaissmaier, 2011:455). In the study of the ways in which decisions are made, the field of behavioral economics developed a variety of heuristics conceptualized to apply across any number of contexts (Gigerenzer and Gaissmaier, 2011).

Several of these have been conceptualized to apply to offenders in offending decisions that reflect the under or overestimation of punishment risk (Pogarsky, 2014; Kahneman, 2013; Piquero, et al., 2011). These have included the heuristics of *representativeness*, *availability*,

anchoring and the '*gambler's fallacy*', which entail either a reliance on stereotypes, restricted information, the failure to adjust behavior in light of new information, or offender assumptions that a break in long term expectations (no arrest) will be corrected in the short term, respectively (Kreager and Matsueda, 2014). Most recently, researchers have included situational factors and measures on the sanctioning environment to broaden factors that may affect "perceptions within the context of a given criminal opportunity" (Pogarsky, et al., 2017:92).

Taken as a whole then, classical deterrence theory has evolved into a neo-classical form under which the marginal deterrence hypothesis has transformed the way in which the theory's punishment principles have been conceptualized to impact offending behavior. In a deterrence mechanism that connects objective risk to perception of risk, the linkage has proven elusive as individual differences in how perceptions are formed and how persons vary in their capacity to be deterred reflect the findings of research examining the relationship (Thomas et al., 2013; Apel, 2013; Anwar and Loughran, 2011; Jacobs, 2010). While deterrence theory has become central to contemporary approaches to crime, this failure has been portrayed as the "dirty little secret" of deterrence (Paternoster, 2010:804).

The question then becomes what can be done to address it? For this study, the solution begins with the movement towards deterrence-based approaches to crime, and specifically with strategies that target street gangs. These groups have historically served as "the provinces, onto which theories developed at the theoretical center are imposed" (Katz and Jackson-Jacobs, 2007:102). In the application of deterrence theory principles, the groups exemplify the challenge in establishing the nexus between sanction changes, perception and behavior as well as provide the opportunity to examine the operation of the marginal deterrence hypothesis in groups increasingly recognized as social networks (Fleisher, 2002). In these networks, the importance

of communication in bridging the gap between punishment and perception reflects in large part a shift in how principles of punishment have been conceptualized, applied, and measured within the context of the policy response to street gangs.

STREET GANG MEANING IN DETERRENCE-BASED RESPONSE

In studies involving street gangs, signifying group meaning represents a difficult challenge for researchers as a number of parties including the media, researchers, policy makers, and politicians have all played a role in shaping their identity, and the problems associated with the groups (Wood and Alleyne, 2010; Weisel, 2002; Ball and Curry, 1995; Spergel, 1995). Differences in methodologies, study populations, theoretical perspectives and research priorities have also contributed to definitional variations, leading some researchers to argue that the lack of a consensus definition impedes the ability to state exactly what a gang is, who are its' members and what they do (Katz and Jackson-Jacobs, 2007; Esbenson, et al., 2001; Ball and Curry, 1995). Still others have insisted that gang definitions and group meanings are largely correct and inconsistent as they have varied by media attention directed at the groups at certain times and places (Ball and Curry, 1995).

In the deterrence-based response to street gangs, a consensus definition marked by a systemic relationship to violence and other serious forms of offending has served to set the groups apart from other criminal offending groups the police encounter (Papachristos, 2009; Klein, 1995; Fagan, 1989). This relationship is one shaped by larger social forces including the "unstable urban social world" in which the street gang is situated, conditioned by groups who function as a "social subsystem… provid[ing]…meaningful social, and perhaps economic structures" [for their members] (Curry and Spergel, 1998: 400-401). This subsystem contributes to a defining street orientation that reflects the group as seen through the eyes of its' members, where cultural and normative aspects of street life -- toughness, competition and violence

predominate (Pyrooz, Decker, and Curry, 2013; Decker, er al., 2008; Decker, 1996; Ball and Curry, 1995).

In many respects, the modern street gang has become a part of the fabric of life in American inner-cities, contributing to an ‘ecology of violence’, “in which beliefs about guns and the dangers of everyday life…shape cognitive frameworks…skewed toward[s] violence” (Fagan and Wilkerson, 1998:107). In this environment, threats of violence serve as a conduit to gang formation and expansionism as well as the establishment of normative violence at the collective or group level (Fagan and Wilkinson, 1998; Decker, 1996). Organizations that feature a group behavior and common action along the axis of purpose, organization or duration, are defined as collectivities. Contemporary street gangs have been reframed as such where violence serves a common action and purpose—defining the world of the gang and its place within it (Decker, 1996, citing McPhail, 1991).

As incidents of violence occur, they are thought to cement requirements for retribution as well as a felt ‘dread of violence’ encapsulated by that expectation (Decker, 1996). This dread underlies the two critical processes of cohesiveness and contagion where internally, gangs become more cohesive from competing group threats and externally, as acts of violence occur, contagion mechanisms spread violence to other gangs and neighborhoods (Papachristos, et al., 2013; Papachristos, 2009; Decker, 1996; Klein, 1971). The shared value and belief systems pertaining to violence and street orientation are reinforced through contagion as inner-city gangs and youth depend on ‘street toughness’ and the commission of violent acts as gateways towards gaining prestige and status within peer networks (Lewis and Papachristos, 2020; Papachristos, et al., 2013; Berg et al., 2012; Fagan and Wilkinson, 1998; Anderson, 1999; Short and Strodtbeck, 1974). Similarly, a gang member who establishes their willingness to use violence demonstrates

their loyalty to their gang while also conforming to "cultural systems that are organized around codes of honor [that] sanction retaliatory aggression as an appropriate response to an affront" (Berg et al., 2012: 365).

As social subsystems generating conflict and violence in "a systemic relationship with other criminal acts" (Fagan, 1989:661), "one of the more enduring, incontrovertible findings in all of criminology to emerge" is that gang members offend more frequently and commit more serious offenses than non-gang members (Tita and Ridgeway, 2007:209). In the processes leading to group violence and to individual offending patterns, it is the criminal activity of the groups that has driven the trend towards deterrence-based responses (Wood and Alleyne, 2010:102; Braga, et al., 2000; Klein, 1993).

MODES OF DETERRENCE-BASED STREET GANG RESPONSE

Two gang approaches— targeted deterrence gang suppression and pulling levers focused deterrence—frame this history (Braga, 2008a; Klein, 1993). Targeted deterrence gang suppression strategies followed as a set of "standard and enhanced enforcement efforts…[seen as]…a more legitimate and justified approach" to the street gang (Klein, 1993:89). As police-led strategies, gang suppression linked principles of specific and general deterrence with a targeted application of enforcement intended to enhance deterrent effects against street gangs and their members (Klein, 1993). Under specific deterrence principles, gang leaders and serious gang offenders were targeted, and under the principle of general deterrence, the sanctioning of leaders was intended to deter untargeted members and at-risk populations from joining the groups (Klein, 1995; Klein, 1993). Targeted deterrence tactics included directed forms of patrol, selective enforcement activities, and zero-tolerance policing as well as street sweeps and multi-jurisdictional task force operations (Klein, 1993; Howell, 2000). Certain efforts evolved to become part of a 'hot-spot' policing approach where particular gang turfs were targeted or

became part of investigations led by prosecutors with the hopes of obtaining higher conviction rates of gang leaders and high-rate offenders (McGarrell et al., 2012; Klein and Maxson, 1996; Klein, 1993).

As the earliest deterrence-based response, Klein (1993) found that the principles of deterrence theory were misapplied in how suppression tactics were implemented. For example, in a strategy that flooded drug and gang-plagued neighborhoods as part of a zero-tolerance approach to law violations—the street sweep was claimed to serve as an effective "general deterrent for actual and potential gang members" (Klein,1993:92). In the largest example, the Los Angeles Police Department sent 1,000 police officers into South Central, Los Angeles where the arrests of 1,453 individuals during a two-day weekend led to claims that the police had sent a strong deterrent message to gang members contemplating further violence (Howell, 2000; Klein, 1995). However, only half of those arrested were gang affiliated, the majority of arrests were made in connection to pre-existing charges, and the sheer volume of arrests necessitated custody changes that resulted in the release of most arrestees (Klein, 1995a). In operation, this indiscriminate use of arrest diluted risk by applying punishment principles "to non-involved populations with little attention to intervening processes [including] "internal group processes and the mutual interactions [that had] set the gangs apart" (Klein, 1993: 93).

As Zimring and Hawkins (1968) described much earlier,

> "For many crimes—particularly when the criminal groups engaged in those crimes are very different from the general population…there will be…a body of persons objectively on the margin of a particular form of criminal behavior…who…are the next most likely to engage in that behavior…[and]…identifiable as similar to one another" (Zimring and Hawkins, 1968:105).

In targeted gang suppression, the general deterrence mechanism would attach to the persons on the margins—would-be gang members—where marginal changes in sanctions would operate to

elevate perception of punishment risk for those considering joining the groups or committing violence (Klein, 1995; Klein, 1993). In this deterrence mechanism critical to police claims of effectiveness, the tactics failed to account for the conceptual importance of population (Klein, 1995; Klein, 1993). While calls followed for more researcher involvement and studies into targeted gang suppression, the strategy remained police directed and the mechanisms of deterrence largely unexplored (Klein, 1995; Spergel, et al., 2003).

The pulling levers focused deterrence strategy followed a different trajectory primarily as a result of larger trends in criminological theory, policing and evaluative research. Pulling lever strategies began as part of the Boston Gun Project, a problem-oriented policing effort designed to identify how illicit firearm markets and a small group of serious youthful offenders were contributing to the pressing problem of youth violence in the City of Boston (Kennedy et al., 1996). "Operation Cease Fire" as it became known, was designed as a collaborative effort under which a criminal justice interagency group working in conjunction with Harvard University researchers, applied quantitative and qualitative techniques to identify the forces driving youth violence (Braga et al., 2001).[11] Part of these techniques included an analysis of the reciprocal incidents of violence within gang factions that were used "to create a social network map of….patterns of conflict and violence among gangs", and to tailor a response to gang offenders driving those patterns (Papachristos and Kirk, 2015:538).

Through their analysis, the Ceasefire working group came to view youth violence as originating from the social networks of chronic gun carrying offenders who made firearms

[11] In Boston, over sixty percent of youth homicides were found to be gang related with sixty-one gangs in Boston accounting for at least 60% of those homicides (Kennedy et al., 1996). Youth violence was also found concentrated amongst a small population of gang-involved youth with frequent offending histories who preferred semi-automatic pistols sourced from an illegal gun market fed from legal retail sales occurring inside and outside of Massachusetts (Kennedy et al., 1996; Braga et al., 2000).

available to other youth through their gang associations (McGarrell et al., 2012). Operation Cease Fire initially consisted of two elements; an effort to remediate the illegal gun market through enforcement against intra-state gun trafficking, and a strategy that intended to elevate the risk of punishment among certain groups of offenders (Braga et al., 2000). As originally implemented, the strategy sought to achieve reductions in youth homicide:

> "By reaching out directly to gangs, saying explicitly that violence [will] no longer be tolerated, and backing that message by "pulling every lever" legally available when violence occurred [including]…strict probation and parole enforcement…stiffer plea bargains and sterner prosecutorial attention…stronger bail terms…and…severe federal investigative and prosecutorial attention on…gang-related drug activity" (Braga et al., 2000: 6).

A central assumption underpinning this approach was that chronic offending gang members would be highly susceptive to a coordinated response by criminal justice agencies and by targeting them, a firebreak in retaliatory violence could be achieved in the hopes of producing longer-term reductions in gun assaults and gun homicide (Braga, et al., 2000).

Pulling lever strategies were designed as a template for researchers and practitioners to adapt to localized crime problems and;

> "In its simplest form, the approach consists of selecting a particular crime problem, such as gun homicide; convening an interagency working group of law enforcement practitioners; conducting research to identify key offenders, groups, and behavior patterns; framing a response to offenders and groups of offenders that uses a varied menu of sanctions ("pulling levers") to stop them from continuing their violent behavior; focusing social services and community resources on targeted offenders and groups to match law enforcement prevention efforts; and directly and repeatedly communicating with offenders to make them understand why they are receiving this special attention" (Braga, 2008a:332).

As instituted over time however, the majority of replications have involved street gangs and gang violence problems in a strategy that has evolved to focus on the "retail messaging" deterrence

component of pulling levers through the use of group-based analytic approaches (Braga and Weisburd, 2012; Braga. 2008a).

However, early pulling lever designs were intended to address the issue of crime displacement, an enduring criticism of place and offender-based interventions (Braga et al., 2014; Eck, 1993). Displacement has been defined as the shifting of crime in response to an intervention or crime control program along "temporal, target, territorial, and functional" lines, and it has reflected concerns that the causes of crime reside with social conditions such as poverty or racial inequality (Reppetto, 1976:168). Because these conditions reside at the macro-social level, police interventions and other "tough on crime" responses are viewed as inadequate responses that may shift crime while also inducing additional financial and social hardships (Western and Muller, 2013; Wacquant, 2009; Rose and Clear, 1998; Sampson and Wilson, 1995).

Framed by displacement concerns, pulling lever evaluations relied on interrupted-time series designs to access crime control benefits in areas where strategies were implemented to geographic 'control' areas where they were absent through pretest and posttest crime rate comparisons (Brag and Weisburd, 2012; Bowers et al., 2011). This approach comported to scientific standards regarding quasi-experimental designs, and secondary goals of improving confidence by controlling for the confound effects of trend, seasonality, and random error as well as observed differences in population size and pre-existing crime trends (Braga and Weisburd, 2012 Weisburd et al., 2006; Weisburd, 2001).

Studies that used this approach reported significant declines. For instance, the original Operation Ceasefire saw decreases in the monthly number of youth homicides (63%), monthly number of citywide shots fired call (32%), and monthly citywide gun assaults (25%) reported in

the year after the effort was fully implemented (Braga, et al., 2000). Later efforts in Lowell, Stockton, Cincinnati, and Los Angeles reported a range of 34% to 44% declines in selected violent crime measures (Braga, Weisburd, and Turchan, 2018:1). Despite these declines, there remained however, "healthy ongoing skepticism regarding the crime control benefits associated with focused deterrence programs among practitioners and crime policy scholars" (Braga, Weisburd, and Turchan, 2018:1).

Underlying this skepticism were concerns with the ability to equate macro-level crime rate changes to interventions aimed at smaller sub-populations of offenders even in situations involving heightened offending by a group of offenders in a localized area (J. McDevitt, personal communication, November 12, 2011). A good example of this is a study by Roman and colleagues (2005) whose impact evaluation was based on disaggregated county crime rate comparisons. In an intervention in which only 38 offenders were targeted, there were no statistically significant differences found in pretest, posttest crime rate comparisons between the county in which the targeted gang had conducted most of its activities and the study's control counties (Roman, et al., 2005). Additionally, quasi-experimental designs failed to resolve concerns that declines could be the result of unobserved variables provided the actual groups were not examined (Braga, Weisburd, and Turchan, 2018). At a theoretical level, the quasi-experimental approach and the frame of crime displacement also diminished the role of deterrence mechanisms and principles of marginal deterrence among the groups targeted in the strategy (Braga, Weisburd and Turchan, 2018; Braga and Weisburd, 2012).

Conceptually, pulling levers focused-deterrence emphasizes a threat-based communication strategy designed to target chronic offenders—backed by a focused enforcement effort that applies sanctions to offenders for continuing their involvement in crime or violence

(Weisburd and Majmundar, 2018; Braga and Weisburd, 2012). This links a general deterrence mechanism from which broader street gang populations are impacted to the generation of a credible, deterrence-based message from both the use and threatened use of punishment (Weisburd and Majmundar, 2018). But as noted, researchers have shifted from the sanctioning component of the strategy to a focused deterrence mechanism described as a form of direct advertising intended to communicate a "retail deterrence" message to small target audiences (Braga, Weisburd and Turchan, 2018). In this message, "knowledge of what happened to others in the target population [is] intended to prevent further acts of violence by gangs" (Braga, Weisburd and Turchan, 2018:211).

In concert with this, researchers have refined the conceptual linkages between focused deterrence, communication and perception through the use of advanced analytic designs that attempt to evaluate crime-reduction benefits at the group level (Braga, Apel, and Walsh, 2014). Braga, Hureau and Papachristos (2013) recently joined an audit of gang violence incidents with a propensity score model that identified targeted gangs, and matched gang controls in order to compare the impact of focused deterrence among the targeted groups. Similar methods extended a 'diffusion of benefit' conceptual framework in order to identify "whether gangs directly targeted by the Ceasefire law enforcement intervention changed their violent behaviors…[and]…whether other gangs that were not directly targeted were deterred" (Braga, Apel, and Walsh, 2014:5).

In this particular study, propensity score matching established control groups while social network analysis facilitated the addition of untargeted groups—linked by incidences of conflict and violence to the targeted groups (Braga, Apel, and Walsh, 2014:5). These untargeted groups were used to advance a concept of 'spillover' originally developed as part of the displacement

phenomenon to explain declines in crime or disorder that occur in areas outside of areas where a formal intervention is implemented (Braga, Apel and Walsh, 2014; Clarke and Weisburd, 1994). In this spillover frame, researchers claimed "a more complete test of deterrence theory" for a strategy whose "goal is to spread the deterrent message far and wide in the hopes that affiliated, unaffiliated, and rival gang members also cease their criminal activity" (Braga, Apel and Walsh, 2014:22). Under this framework, researchers also used a growth curve analysis to compare gun violence trends among targeted, untargeted, control gangs where a statistically significant reduction in reported shootings among targeted and untargeted gangs was found (Braga, Apel and Walsh, 2014).

While these recent studies add to the body of evidence in support of deterrence-based approaches to street gangs, there is a disconnect between the concepts developed in this well-supported strategy and a marginal deterrence hypothesis that exists in a state of relatively unsatisfactory empirical support (Apel, 2013; Tonry, 2008). Under the hypothesis, "deterrence theory is a social psychological theory of threat communication in which the causal chain runs from the objective properties of punishment through the perceptual properties of punishment to crime" (Paternoster, 2010:785). However, in the earlier pulling lever studies, the chain was hidden behind a wall of displacement concerns, and in the concept of spillover, a proxy measure now serves for unobserved connections between punishment, communication and perception among targeted and untargeted gangs.

In his comments on the current state of criminological knowledge, Smangs (2010: 610) noted that the central question in many criminological theories "is why individuals commit crime or differences in criminal behavior between individuals", and a result, the individual serves as the unit of analysis. However, in many criminological theories including deterrence, the actual

“level of explanation” rests with mechanisms at the interpersonal and interactional level (Smangs, 2010:610). This is particularly the case in deterrence-based strategies, which “attempt to make sanction risk certain and salient to a selected high-risk group” (Durlauf and Nagin, 2011:36) in enforcement strategies that rest with the “*behavioral response to the perception of sanction threats*” (Italics added) (Nagin, 2013:204). Because “police cannot directly manipulate perceptions”, the challenge for any deterrence-based strategy lies in establishing that adjustments in individual perception occur in response to changes in enforcement or threats designed to elevate objective risk (Nagin, 2013:204).

GANGS AS SOCIAL NETWORKS

This challenge requires an approach that can model distinctions between the objective and subjective properties of punishment in order to identify how threat communication bridges the gap in street gangs (Geerken and Gove, 1975). These groups have been long recognized as “social networks composed of individual gang members” (Fleisher, 2002:612) that serve “to generate trust, establish expectations for behaviors, and reinforce social norms” related to criminal behavior and violence (Haynie, 2002:103). These networks similarly determine or constrain behavior based on the location of individuals within the structure while providing conduits for communicating and carrying out the activities of the group (Malm and Bichler, 2011; Morselli, 2009; Morselli, 2005; Fleisher, 2002). It is somewhat surprising therefore, that most gang studies “have failed to capture the entwined nature of social and spatial networks as correlates of gang behavior” (Papachristos, et al., 2013: 418). In those that have, new understandings of gangs and the gang violence phenomenon have been achieved (Papachristos, 2009; Papachristos, et al., 2013).

For instance, in a study of gang homicide in Chicago, network patterns revealed that what was considered an interpersonal crime of violence, was the actual result of a "structured set of social relations in which violence [worked] its way through a series of connected individuals… as competing groups [jockeyed] for positions of dominance" (Papachristos, 2009:75-76). The aggregate patterns found by Papachristos (2009) in Chicago gang homicides reflected a collective process of conflict previously unidentified. Similarly, social network analysis has facilitated the identification of linkages between a gangs' association with geographic sections of' 'turf", prior and future gang conflict, and higher incidences of violence for spatially proximate gangs (Papachristos, et al., 2013). In this regard, street gangs used violence to protect their interests in drug markets and in defense of more synergistic group properties such as the collective identity derived from the group's association with turf (Papachristos, et al., 2013).

In an essay written over twenty years ago, Tonry (2008:280) noted that "useful research on deterrence will have to become much more nuanced" if it hopes to provide answers to questions pertaining to whether legal threats are effective in preventing crime, whether would-be offenders perceive sanction changes as meaningful and in answering how individuals differ in their susceptibility to changes in legal threats. In street gangs serving as the province for deterrence theory, the science of social networks offers the potential to uncover the theoretical mechanisms underlying perception as it places importance on the connections between individuals, and the interactions that take place between them in influencing behavior. As McGloin and Kirk, (2010: 210) have noted, "social network analysis is more than a set of methods…[it]…is an orientation toward the understanding of human behavior that focuses on the importance of social relations" (McGloin and Kirk, 2010b: 210). This orientation aligns with street gangs "embedded in a complex web of social relationships that cut across social,

geographic, and even virtual space", and with network methods that are well-suited to examine them (Sierra-Arévalo and Papachristos, 2017: 374). By joining this orientation to the study of deterrence, a new methodological approach becomes available to examine the nexus between sanctions, perception and behavior. As outlined in the next chapter, this network approach places the measurement of communication and perception with the social ties between individuals.

THE SCIENCE OF SOCIAL NETWORK ANALYSIS

Historically, gestalt theory provides the foundation for the social network perspective (Scott, 2001). Gestalt theory asserts that "there are contexts in which what is happening in the whole cannot be deduced from the characteristics of the separate pieces, but conversely; what happens to a part of the whole is, in clear-cut cases, determined by the laws of the inner structure of its whole" (Wertheimer and Reizler, 1984: 311). This perspective grew from frustration with a rationalistic scientific method that separated social phenomenon into constituent parts for study, and reconstituted them under the auspices of advancing scientific understanding and human knowledge (Wertheimer and Reizler, 1984). Yet in seeking to penetrate the core of phenomenon, the scientific method resulted in the production of "information and connections…[but] somehow what [was] most crucial, the most essential, and the most vital…[was] lost (Wertheimer and Reizler, 1984: 308).

Gestalt is an attempt to study nature in a way that will produce a deeper understanding through an explicit focus on the whole, determined by the nature of its constituent parts (Scott, 2001). As a philosophy of science, the development of the network perspective is derived from Gestalt's incorporation of individual and social psychology. In psychological research under Gestalt, emphasis was placed on "the organized patterns through which thoughts and perceptions

are structured" (Scott, 2001: 9). These organized patterns are regarded as systems that possess properties distinct from their parts, yet these system properties also determine the nature of those parts (Scott, 2001). Hence, human thought and perception are part of an inner process whereby objects are "preconceived within the complex and organized conceptual schemes of the human mind…[yet] the objects of the world are not perceived independently…but are, in a fundamental sense, constituted by them (Scott, 2001: 9)". Therefore, thoughts and perception are understandable only if the systems giving rise to those perceptions are understood. For example, in the preferences and desire for products, consumer choice has been found to be shaped less by the desire of individuals and more so by a perception of need created by images meant to manipulate and influence choice (Lee and Choo, 2019).

Flowing from and rooted to the concept of systems, social and social psychological researchers have examined the role of groups and organizations in influencing individual behavior as well as the way in which these structures are impacted through their constituent members. This research began in earnest with prominent gestalt researchers Kurt Lewin and Jacob Moreno with Lewin focused on small groups, group dynamics, interpersonal relations and cliques and Moreno primarily interested in the internal structures of groups (Scott, 2001; Wasserman and Faust, 2004). Over time, three major streams of research developed to contribute to a scientific tradition of network analysis: "the sociometric analysts, who worked on small groups…and graph theory…[a Harvard group]…who explored patterns of interpersonal relations…and 'cliques' and the Manchester anthropologists, who built on both strands to investigate the structure of 'community' relations in tribal and village societies" (Scott, 2001:7).

In the realm of social psychology, Lewin (1951) in particular examined how social perception and group structure were determined by a larger 'field' of social forces while Moreno

(1960) focused on what he termed 'sociometry'; the study of the evolution and organization of groups as well as the position of individuals within those group over time (Scott, 2001). Moreno's major contribution to network analysis was the sociogram, a visual graph under which inner group structures could be diagramed and studied (Scott, 2001). A sociogram is comprised of two components; points or in modern terms, nodes or actors, and social relations represented as lines or ties (Wasserman and Faust, 2004; Scott, 2001). The simplest form of a sociogram for individual (A) illustrates the conceptualization of the individual and their relational network within geometric space.

The Moreno sociogram may appear novel to our time, however it would empower previously vague concepts such as the 'web of relations' and the 'social fabric', while enabling the development of graph theory, a mathematically based paradigm used to postulate and study the structure of relations (Scott, 2001).[12] Equally important, the visualization of relations as lines enabled researchers to observe the channels of communication on which social influence is predicated (Wasserman and Faust, 2004). In a topological sense, individual actors within graph theory become nodes or vertices, whereas the lines connecting nodes or vertices become edges that represent either direct or indirect interdependency. The paths running between points tie them together and form patterns of paths resulting in discrete regions that are separated from one another by the absence of a path between regions (Wasserman and Faust, 2004; Scott, 2001).

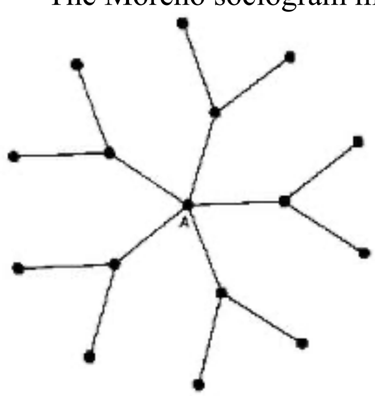

Figure 2: Moreno Sociogram

[12] Moreno's importance to theoretical thought and influence in the field of network research is understated here. His approach was heavily influenced by the philosophical perspectives of Simmel, Weber and Tonnies, and reflected the view that interpersonal relations give rise to the establishment of large scale 'social aggregates' or groups that serve to influence individual opinion, behavior and outcomes (Wasserman and Faust, 2004; Scott, 2001).

In figure 3, a hypothetical network between actors connected through friendship ties is depicted. This figure indicates phenomenon observed in naturally occurring social networks.

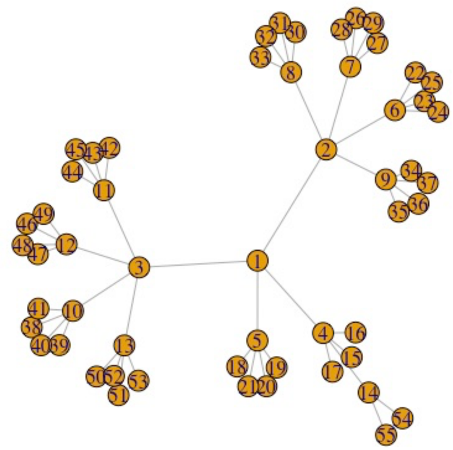

Figure 3: Example of a Friendship Network

The paths that run between points or nodes form patterns that result in clustering of points as well as an absence of paths between regions (Wasserman and Faust, 2004; Scott, 2001). The points or nodes in a graph represent any number of actors including "companies, sports teams, universities, governmental departments, or any other social unit (e.g., gangs)" (Sierra-Arévalo and Papachristos, 2015:158) while ties, lines or paths represent "social constructs produced on the definition of the situation made by group members" (Scott, 2001: 53). For example, graph theory has been used to examine networks of cardiologists based on their use of new medical procedures, to examine connections between academics in their peer networks based on journal publications, or in tracing the early Portuguese empire based on its' evolving family relations (Boracci and Giorgi, 2017).

After Moreno's introduction of the sociogram, Kurt Lewin further developed field theory to encapsulate the social space in which groups exist and operate as a dynamic environment (Scott, 2001; Moreno, 1960). Lewin (1951) and other researchers were interested in how groups change over time and what forces produce change both internally, and externally within the larger field in which groups were situated. Field theory also introduced a mathematically based, topological approach to the study of human behavior under which "interdependence between group and environment in a system of relations" could be assessed based on external ties that

represented influence and change from the larger social environment (Scott, 2001: 11). This led directly to the application of mathematical axioms with the patterns of relations created by the lines connecting actors. These axioms form the empirical framework of social network analysis enabling the modeling and predictions necessary to properly develop network-based theory (Wasserman and Faust, 2004). The foundation of social network analysis is the dyadic relationship, which captures the relationship between actors in one of three states: undirected,

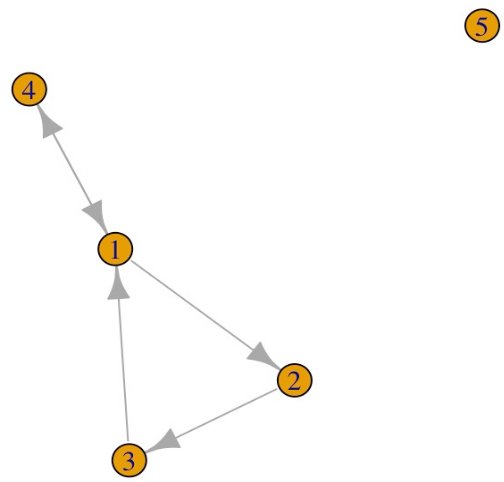

Figure 4: Directional and Reciprocated Dyadic Relations with Social Isolate

directed and reciprocated. In the figure below, the basic forms of dyadic relationship are indicated with directed relations observed between actors 1, 2, and 3 and reciprocated relations observed between actors 4 and 5.

From these relationships, cliques arise defined as "a cohesive subgroup…of actors connected through many direct, reciprocated choice relations that enable them to share information, create solidarity and act collectively" (Knoke and Yang, 2008: 72). These relationships simultaneously create networks, and a social system comprised of "a set of interrelated units [that] provide stability and regularity to individual behavior" (Hoffman, 2011: 39). Empirically, graph theory

provides for measuring the number and direction of relations, the identification of important subgroups, the examination of the location and importance of individual actors, and assessing the relative strength or frequency of relationships among actors (Scott, 2001; Sarnecki, 2001).

In mathematical terms "graph theory defines a social network as the bounded set of actors and the collection of relations between them" (Sierra-Arévalo and Papachristos, 2015:158). In this way, values are assigned to both actors and relations in such a way that themes of social dependency can be accessed. Figure 5 provides an illustrative example for a four actor network describing vertices and ties.

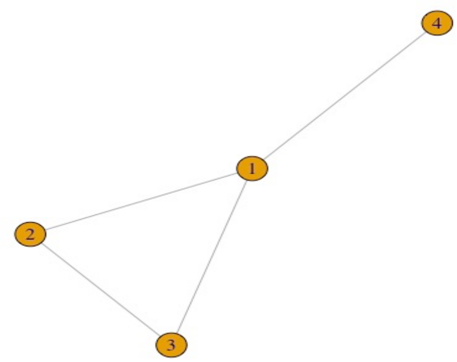

Figure 5: Graph Theory: Undirected network of a set of 4 actors or vertices, V = {1,2,3,4} and set of relational ties (1,4) (2,1), (2.3)}.

Graph theory requires social network data consisting of one or more relational measures from which analysis can determine patterns or structures of ties in a network (Sierra-Arévalo and Papachristos, 2015). The ties that determine structure produce structural influence on the behaviors, opinions and attitudes of network actors (Lusher et al., 2012; Wasserman and Faust, 1994). Variable data in the form of actor attributes are also required to examine their role in creating structural ties and conditioning the effects of structure on behavior opinions and attitudes (Lusher, et al., 2012).

The implication of this analytic approach is that "actors and their actions are viewed as *interdependent rather than independent*" (Wasserman and Faust, 2004: 89, emphasis in original). In practice then, graph theory requires the inclusion of concepts and information on relationships that captures the fundamental assumptions of dependency sourced from the structures of social

networks (Wasserman and Faust, 2004: 89). This is a departure from independent observation assumptions that permeate the study of gangs and deterrence in ordinary least squares analytic models.[13]

In the joining of a social network perspective to the study of deterrence in gang-based efforts, structural relations become the key orienting principle for examining the marginal deterrence hypothesis and the effects of marginal punishment changes on behavior (Knoke and Yang, 2008). As a consequence, the level of explanation in a networked study of deterrence is placed at the interactional level with the social ties between actors where communication and perception processes operate in the gang setting according to the principles of deterrence theory. The next section elaborates on this networked theory of deterrence, which motivates the assessment of FBI's efforts to combat the street gangs in Lynn.

A SOCIAL NETWORKED THEORY OF DETERRENCE

The need for a networked theory of deterrence begins with the limitations of existing research and ends with the application of a diffusion of innovation framework under which principles of punishment can be accessed for their impact on perception. While recent pulling lever evaluations recognize that street gangs "can act as [a] vehicle for transmitting the actual risk to other offenders [whenever] sanctions for noncompliance are applied" (Braga, Weisburd, and Turchan, 2018:7) there remains a void in how communication takes place and how effective threats of punishment are in changing the perceptions of gang members. In this way, the "gap between the message as delivered and the message as received" remains a key obstacle to claims of effectiveness in deterrence-based strategies (Klein, 1993:91). In addition, it remains unclear

[13] The use of actor variables in network studies does not comport to 'variables by cases' analyses where independence between observations is a critical assumption of OLS regression (Wasserman and Faust, 1994; Allison, 1999).

in the current state of research whether the targeting of high-rate offenders leads to the generation and transmission of more credible messages of deterrence given the groups are organized around norms supporting offending and street violence (McGloin and Kirk, 2010; Reiss, 1988).

The network perspective in this study is derived from three processes related to peer influence and behavioral dependence, communication and social change. While each of these processes have been developed in separate domains of network research, they join together in a network intervention framework designed to induce change. For example, network interventions have become integral to public health strategies designed to address negative health behaviors such as excessive drinking, smoking and drug use (Latkin, et al., 2013; Valente, 2012). In such strategies, officials seek to alter the social norms that are conducive to these behaviors by using the structure of networks to introduce change, such as preventing HIV infection among injection drug users by prioritizing clean needle usage (Latkin, et al., 2013).

This framework has important meaning for a marginal deterrence hypothesis reconceptualized to function through the structured set of ties within the networks of street gangs. At the outset, a 'network intervention' reflects assumptions that individual behavior is affected through opinions and behaviors of those with whom individuals have personal connections (Valente and Davis, 1999). This concept of peer influence reflects the reality that we value the opinions of those with whom we have social relations, and how we conform our behavior to maintain acceptance of our peers (McPherson, et al., 2001). While peer influence has provided the foundation for differential association and social learning theories of crime, in the network intervention frame, it joins with network structure to become the primary driver of

individual beliefs, opinions and decisions to change their behavior (Valente and Davis, 1999; Sutherland, 1947; Burgess and Akers, 1966).

In this regard, network interventions often represent "purposeful efforts to use social networks…to generate social influence, accelerate behavior change…[and]…achieve desirable outcomes among individuals" (Valente, 2012:49). In the majority of cases, interventions are initiated by external change agents who seek to accelerate behavioral changes from outside the social network structures through opinion leaders (Valente and Davis, 1999). These individuals possess higher levels of social connections who are often viewed as popular actors within their peer networks (Valente and Davis, 1999). In addition, because of their higher level of connections, opinion leaders are structurally positioned to influence group member behavior towards that sought by the external agent (Rogers, 2002; Valente and Davis, 1999). In the street gang, these principles have been embodied in the notion of social capital derived from the connections gang members have to others in gang networks, and in the concept of gang embeddedness, which reflects "dense criminal network ties, leadership positions within the criminal network and increased illegal earnings" (Pyrooz, Sweeten and Piquero, 2013).

A related process in the network intervention framework concerns the elaboration of peer influence and social ties into a structure referred to as communication flow relations. Flow relations conceptualizes the ties in a social network as forming the channels in which "the exchange or transmission of…information among" individuals take place (Shumante et al., 2016:98). The information conveyed through these channels in reference to behavioral change—*including the explicit or implicit advantages in doing so—represents the keystone of interventions designed to change behavior* (my italics) (Valente, 2012). In gangs "whose identity is tied to the streets and whose internal dynamics surrounding loyalty, protection,

reputation, and cohesion generate individual and collective behavior", these flow relations serve to support the group processes that underlie violence (Lewis and Papachristos, 2019). As network structures for deterrence, communication flow relations would instead operate to pass objective punishment risk information from targeted actors to other gang network members consistent with the intent of authorities to elevate objective punishment risk.

The third component of the intervention framework concerns an important theoretical elaboration—diffusion of innovation (Valente, 1995). Diffusion of innovation traces the spread of new ideas and behaviors through the communication flow networks by conceptualizing the process of change as a function of time and peer influence (Valente, 1995; Poole, 2013; Greenan, 2015). Diffusion theory effectively joins the elements of communication and peer influence with time to address limitations with cross-sectional studies of network intervention that failed to capture the dynamic nature of change (Rogers, 2002; Poole, 2013).

As Rogers (2002:6) describes, diffusion is "a kind of social change, defined as the process by which alteration occurs in the structure and function of a social system. When new ideas are invented, diffused, and are adopted or rejected, leading to certain consequences, social change occurs". Examples of diffusion vary, but they provide a networked understanding for how and why people change behavior in response to new ideas and information originating from within or outside social structures (Rogers, 2002). For instance, a diffusion study of scurvy control in the British Navy demonstrated the power of opinion leadership in changing behavior (Rogers, 2002). From the first discovery and reporting of the benefits of Vitamin C by a British Captain, it took the Navy nearly 100 years to implement changes to dietary practices. The underlying reason for this delay rested with the fact that the captain was not positioned in the social structure to influence others. When the benefit was introduced by an opinion leader,

dietary practices quickly changed (Rogers, 2002). As another example involving terrorism, a diffusion study pointed to the importance of religious ties in spreading the military innovation of suicide bombing (Horowitz, 2010). Previous studies had linked the rise of the suicide bombing to local conditions where groups such as Hezbollah and Al Qaeda were embedded; however, the spread of the tactic was found in a diffusion analysis to be facilitated by the social connections between the groups, and in particular, religious leader ties that bridged them (Horowitz, 2010).

Diffusion studies have also been used to examine the spread of birth control pills and the use of condoms among women in developing countries, and to examine factors that conditioned the adoption of innovative farming techniques in and across South American villages (Rogers, 2003; Rogers, 2002; Valente, 1995). Birth control and farming techniques are classic interventions designed to diffuse widespread behavioral changes through the injection of new ideas and practices within existing social structures. In both cases, the United Nations Educational, Scientific, and Cultural Organization (UNESCO) served as an external change agent in marketing and technological innovation campaigns designed to address issues of women's reproductive health and famine, respectively (Rogers, 2002). As a behavioral change process, network diffusion is often the result of a "a series of events that unfold through time to eventuate in some outcome" (Poole, 2013:380). This outcome is further influenced by causal and contextual factors, which determine how change occurs (Poole, 2013). In the network intervention frame applied in this study, criminal justice officials function in the role of change agents. The use of deterrence-based sanctions and leveraging of opinion leader influence by these agents is intended to initiate widespread behavioral change within the social network structures of street gangs. In fact, the targeting of gang leaders and other influential members connects to the expressed purpose of deterring other group members from committing violent

acts and gang-related offenses (Weisel, 2002). In the figure below, the role of law enforcement as change agent is illustrated within the diffusion framework.

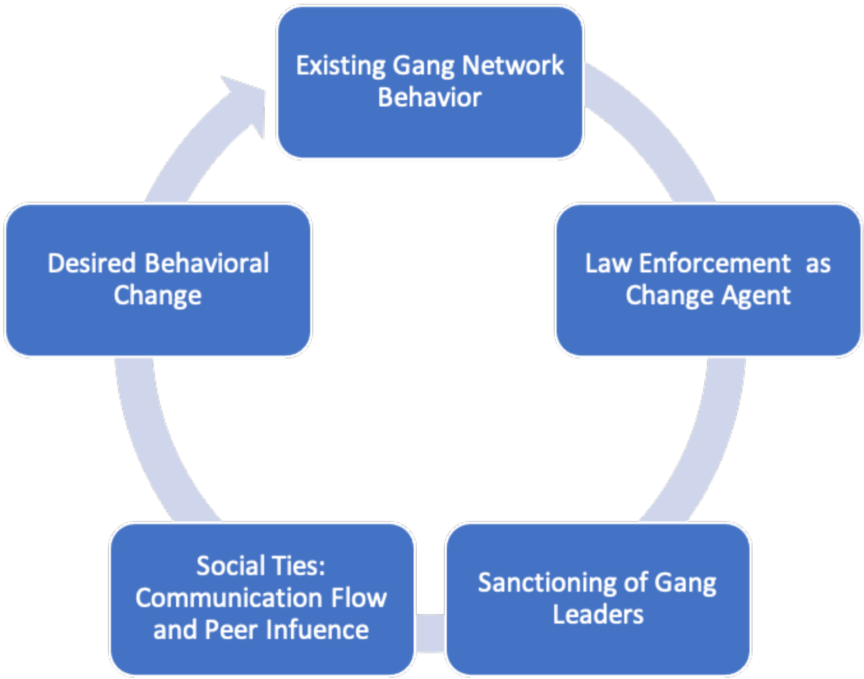

Figure 6: Diffusion of innovation framework for law enforcement as network change agents

The marginal deterrence hypothesis also places communication at the heart of a general deterrence mechanism whose effectiveness is determined by the perceptions of the would-be offenders (Cook, 1980; Nagin, 2013). When joined with the view of social network structure as communication flow relations, the general deterrence mechanism becomes grounded to the exchange of objective risk along the structured set of socials ties in the gang network. While individual social ties serve as the conduits for risk information to be transferred within the gang's network structure, these ties also provide for traditional channels of peer influence.

As an extension of peer influence and communication processes, diffusion is a transformative frame that accords with arguments "that police interventions provide an effective approach for gaining both specific and general deterrence against crime" (Braga and Weisburd, 2012:324) by engendering risk apprehension among small populations of networked offenders

through focused and sustained deterrence campaigns. The four elements of every diffusion campaign intended to alter behavior ultimately concern "the innovation [itself], communication channels, time, and the social system" (Rogers, 2003:10). By placing the level of explanation with social ties, the marginal deterrence hypothesis becomes aligned with these elements both conceptually and analytically. Sanctions intended to elevate objective risk, communications intended to convey that risk, and their perceptual risk effects all occur over time within the social system of street gangs.

In this way, silos that have separated incapacitation, specific and general deterrence punishment effects are deconstructed as each effect becomes part of a diffusion campaign that reflects the sequence of sanctioning activity. When joined with a diffusion of innovation analytic model, the current study of gangs and deterrence advances hypotheses related to communication, peer influence and offending decisions in light of individual differences in social ties, offending histories, demographics and punishment experience. This analysis is consistent with assumptions of network dependency, and a unit of measurement—social ties—that establish the communication flow structure depicted below. The red nodes in the graphs represent actors charged federally and the yellow nodes indicate state charged individuals: reflecting the entry of targeted actors at the time points in which they were sanctioned by the FBI's North Shore Gang Task Force. When these actors enter, they bring along cooffending relations identified through the study's sampling procedures described in Chapter Three. These ties conceptualize channels upon which information on risk would be communicated while serving as a proxy measure for evaluating the impact of risk on individual perception through actor decisions to desist from gang offending. This structure further provides for a longitudinal study design that allows for "the innovation to diffuse adequately" (Greenan, 2015: 147).

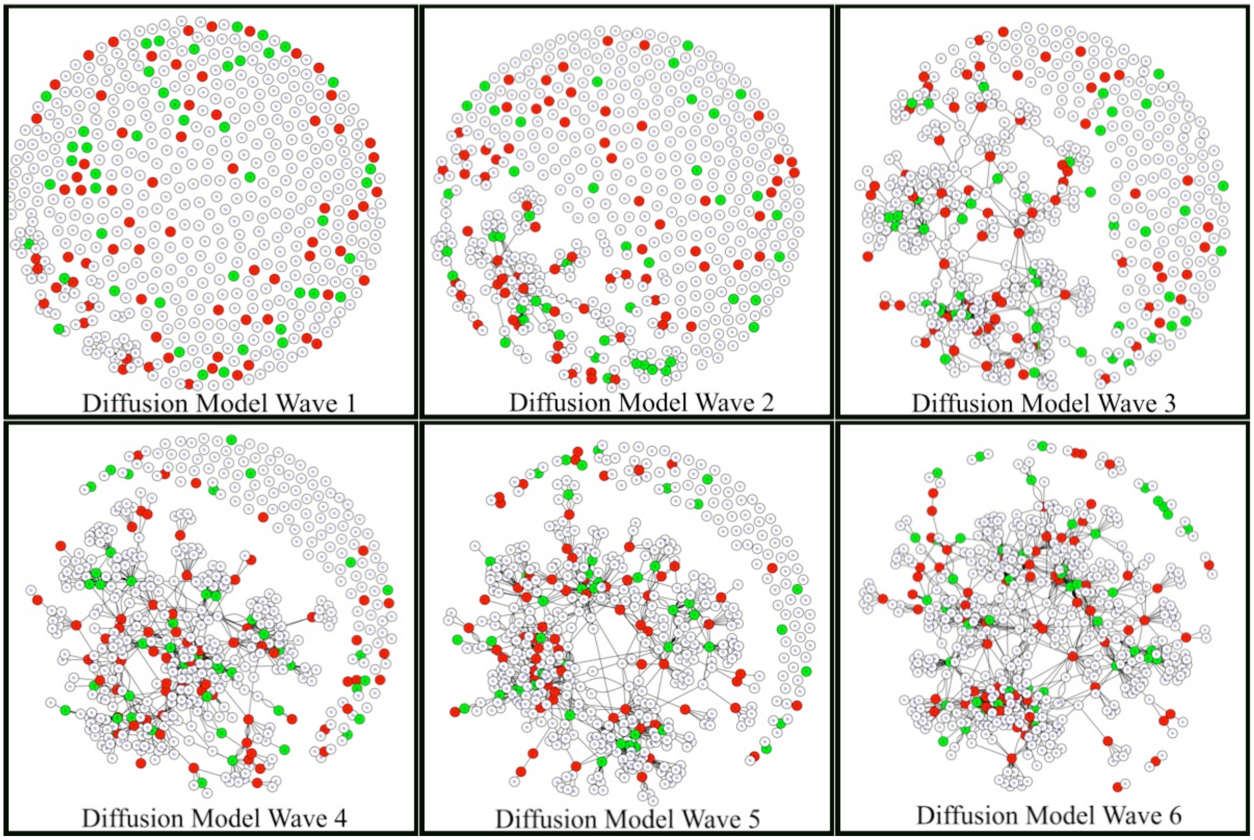

Figure 7: Communication Flow Relational Structure of Lynn Street Gangs

STUDY HYPOTHESIS

In the context of the study's diffusion framework and the use of a Stochastic Actor Oriented Model, the following hypothesis are examined in this research:

H_0: Targeted sanctions resulted in no observed change in offending behavior of targeted gang actors.

H_1: The operations in Lynn did result in observed offending declines among targeted gang actors. If H_1 is true, then the study will evaluate the following hypotheses:

H_2: Was the hazard risk for desistance influenced by the social ties between targeted gang members and the untargeted individuals, or was there a general increase in hazard of desistance irrespective of social tie connections?

H_3 Did the structured prosecution of federal enterprise crimes by the North Shore Gang Task Force, and the imposition of more severe sanctions enhance the hazard risk of adoption for federally convicted gang members? This study evaluates these distinctions first by comparing the hazards between the two classes of targeted members, and second, by evaluating hazards for untargeted members conditioned by connections to federal or state convicted members.

H_4 Was the diffusion of innovation affected by actor attributes including race, prior offending history and age? This hypothesis explores whether adoptions of desistance were conditioned by individual differences outside of any observed network structural effects.

The Stochastic Actor Oriented Model (SAOM) discussed in the following chapter, will also examine the network dynamics underlying the structure of the Lynn gang network before, during, and after the periods when the groups were subjected to FBI enforcement efforts. The SAOM is a class of coevolution model rooted in the assumption that social networks act as both a constraint and as a consequence of behavior (Leenders, 1997). In this dependence, two processes are at the heart of a network tradition comprised from social selection studies that have examined " mechanism[s] by which individuals adjust their relationships in response to the social context, their own behaviors, and their peers' behaviors [and] social influence studies [that] looked to processes [by which] individuals change their behavior or attitudes in response to (the behavior or attitudes of) the peers" (Veenstra, 2013: 399).[14] The Stochastic Actor Oriented

[14] Selection effects are reflected in the creation of social ties beginning in childhood where nonrandom sorting takes place according to actor attributes such as age, gender, race, and income.

Model (SAOM) was developed to improve the study of dependence in social selection and social influence processes by combining them in a coevolution model (Steglich, et al., 2010).[15]

These models have been used frequently in the study of youth networks and peer delinquency; an area in which social selection and social influence are suspected to interact in influencing network formation and delinquent behavior (Greenan, 2015; Veenstra, et al., 2013). By modeling both processes simultaneously, studies have indicated that selection plays an oversized role in delinquent behavior through its' influence on the formation of friendship ties (Greenan, 2015; Veenstra, et al., 2013).[16] In terms of this study, it is uncertain how these processes interact as this is the first case where the model has been applied to a network of cooffending relations. The goal of this research is therefore modest in exploring the properties of this network through standardized Stochastic Actor Oriented Model measures. In the following chapter, the Stochastic Actor Oriented Model is presented in detail. This detail is required as it provides the foundation for this study's diffusion of innovation model. This model is then presented alongside a discussion of how it will be applied in testing the study's deterrence-based hypotheses under the network-based diffusion framework.

[15] This improvement connects to the criticism of network autocorrelation bias; a phenomenon arising when the processes are studied in isolation leading to potentially misleading results (Steglich, et al., 2010).
[16] Attributes such as class assignment and gender are often evaluated in these models for their effects on selection. The reasons for doing so are discussed in more detail in the next chapter.

CHAPTER 3

ANALYTIC STRATEGY

As outlined, this study applies social network analysis to understand the communication of deterrence within the gang networks in Lynn, Massachusetts. To accomplish this, an analytic strategy employing a Stochastic Actor Oriented Model addresses the four hypotheses previously described within the diffusion of innovation framework. The Stochastic Actor Oriented model allows for the "complete network structure as well as relevant actor variables to be studied as joint dependent variables in a longitudinal framework where the network structure and the individual attributes mutually influence one another" (Steglich et al., 2010: 330). Three statistical assumptions simplify the causal processes for estimating network and actor influence in the Stochastic model (Snijders, et al., 2007). These are: (1) observations at discrete time points $t_1 < t_2 \ldots < t_m$ "are the outcomes of an underlying process $Y(t) = (X(t), Z_1(t), \ldots, Z_h(t))$ that is a Markov process with continuing time parameter t" (Snijders, et al., 2007:46); (2) actors act independently given the current state of $Y(t)$ meaning that changes to network or behavior that may occur because of mutual bargaining are not allowed; (3) the decision on changing network ties or behavior are independent and occur as part of a mini-step process where actors are restricted to making only one change at a time to the vector of ties, vector of behavior and behavioral variable vector. [17]

This mini-step process provides for parsimony in approximating the co-evolution process of network and behavior while relaxing the numbers of observations required on networks and behavior to initiate the stochastic approximation process (Snijders, et al., 2010). Stochastic

[17] Current states are represented in the following vectors; $X(t)$ network, $Z_1(t)$, behavior, and behavioral variables $Z_h(t)$, which includes individual covariates $v_h = v_{h1,\ldots,}v_{hn}$ and dyadic covariates $w_h = (w_{hij})_{1\le i,j\le n}$, which can be constant or time variable (Snijders, et al., 2007).

estimation of these models is made by the Methods of Moments estimator, where parameter estimation is based on one observed statistic for each estimated parameter (Snijders et al., 2007).[18] Stochastic Actor Oriented Models are 'actor-oriented' in the sense of examining change from the perspective of the actor as they seek to maximize social tie benefits based loosely in a rational-choice model (Ripley et al., 2018). Conceptually, this represents a sense of human agency that these models evaluate through a variety of measures pertaining to the creation, maintenance and dissolution of network ties (Ripley, et al., 2018; Schaefer, 2017). In the current study, agency will reflect the establishment of ties consistent with an actor's decision to maximize their benefit within a cooffending relationship-based network. The measures that evaluate this process will offer insights into actor preferences within an evolving network structure that spans a 13-year time frame.

The Stochastic Actor Oriented Model relies upon the observed directed relations between senders $i \rightarrow j$ and receivers $j \rightarrow i$, referred to as ego and alter respectively, in proposing a mini-step process where network evolution and behavior evolve according to a rate-of change function and where network dynamics are driven by an objective function. This results in "the outcome variables for [joint evolution models being] the changing network and changing actor behavior—which may be called endogenous, since they evolve as a function of each other" (Steglich, et al., 2010: 346). The basic coevolution model therefore consists of four components: two rate functions that express the amount of change from observations of the network and behavior and two objective functions that express the direction of that change (Veenstra, et al., 2013). This results in a model where "any imputed sequence amounts to the repeated identification of a focal actor (ego) who gets the opportunity to make a change to his or her tie or behavior (or to make

[18] Stochastic Actor Oriented Models use iterative algorithms to approximate network solutions over the unobserved periods and as a result, these models do not require fixed time observation points (Snijders, et al., 2010).

no change), and the identification of the change outcome" (Veenstra, et al., 2013:402). As a result, rate functions further identify the frequency with which actors may make changes in ties or behavior while objective functions parameterize outcomes through a multinomial logit choice model (Veenstra, 2013).

In the basic coevolution model, the objective function for network dynamics takes the linear form (Snijders, 2017:18):

$$\boldsymbol{f}_i^{net}(x) = \sum_{K=1}^{L} \beta_k^{net} S_{ik}^{net}(x)$$

where β_k^{net} are internal rate parameters and the 'effects' $S_{ik}(x)$ included from the point of view of actor i, include actor outdegree, reciprocated ties and a dependency assumption, typically that of a triadic formulation:

$$\begin{aligned} S_{ik}(x) = {} & \textstyle\sum_j x_{ij} \text{ (outdegree)} \\ & \textstyle\sum_j x_{ij}\, x_{ji} \text{ (reciprocated ties)} \\ & \textstyle\sum_{j.k} x_{ij}\, x_{jk} x_{ik} \text{ (transitivity)}^{19} \end{aligned}$$

Objective rate effects for behavior are represented in the basic coevolution model:

$$\boldsymbol{f}_i^{beh}(x,z) = \sum_{K=1}^{L} \beta_k^{beh} S_{ik}^{beh}(x,z)$$

Where β_k^{beh} are base rate parameters and $S_{ik}^{beh}(x,z)$ are behavioral effects. These include a linear behavioral effect $S_{i1}^{beh}(x,z) = z_i$ where z_i indicates an ordinal level, dependent behavioral variable of actor i , and a quadratic shape of the behavior upon itself $S_{i2}^{beh}(x,z) = z_1^2$. This

[19] Outdegree and reciprocated ties are two universally observed structural properties of social networks required for estimation. Transitivy is a measure of balance in the triadic group structure. These triadic measures are included as an indication of network closure: a universal aspect of social network structure. Other triadic structural effects such as 3cycle are often evaluated in models during the estimation process (Block, 2015).

quadratic effect identifies the attractiveness for the actor to change behavior conditioned by the existing level of behavior (Ripley et al., 2018).

Extensions of the stochastic model logically connect to information that actors would consider in their network and behavioral decisions through effects “determined by subject-matter knowledge, available scientific theory and formulation of research questions” (Snijders, 2017:7). These effects function as “independent (exogenous) variables [that] can be individual or dyadic, changing or unchanging” (Steglich, et al., 2010: 346). For example, in the case of network studies on peer delinquency, classroom assignment is included as an effect conditioning the formation of friendships because of the degree to which actor choices would be conditioned by their classroom interactions (Steglich, et al., 2010). Additionally, network statistics are frequently included in stochastic models to evaluate network dynamics, and the creation of social ties. For example, actor degree is an important statistic that captures natural tendencies for popular network actors to attract more ties from others in a network or for more active actors to create more ties within the network (Snijders, 2017:7). These effects, referred to as alter and ego, respectively, can also interact with specific actor attributes such as gender or race to evaluate questions related to the impact of gender on the pattern of ties found in a friendship network (Veenstra, et al., 2013). The alter and ego effects can also be interacted with behavior to evaluate its’ impact on network dynamics to the degree to which it impacts an individual’s popularity or sociality in accordance with principles of behavioral dependency (Greenan, 2015; Veenstra, et al., 2013).

In this study, the stochastic model examines how the members of the gang networks in Lynn, Massachusetts are connected, how their connections evolved over time, and what attributes were important for gang members in their decisions to create ties. In addition to any

insights that this will offer on Lynn gang network dynamics, the SAOM provides the analytical foundation for the study's diffusion of innovation model. This model is used in the study to examine how members of the Lynn gangs responded to the enforcement campaign being waged by the North Shore Gang Task Force, and what elements of the network or attributes of the actors conditioned the individual response to sanctions and the threat of punishment.

DIFFUSION OF INNOVATION MODEL

This diffusion of innovation model used in this study was developed to trace the adoption of behavior while simultaneously accounting for network dynamics underlying the processes of social selection and social influence (Greenan, 2015). The diffusion model represents a special class of SOAM. It combines the parameters of the basic Stochastic Model described above with a Hazard Model that traces the diffusion of innovation as a function of contagion while transforming the objective behavior rate function (Ripley, et al., 2018; Greenan, 2015). In this study, this means that the coevolution of behavior and gang network dynamics can be modeled simultaneously with the tracing of the gang member responses to sanctions and threats of punishment. Contagion in diffusion studies generally refers to the amount of time it takes for an innovation to be adopted, which may be conditioned by individual characteristics, the social network itself, and the actors place within it (Greenan, 2015). "For example, those with many connections in the network may be more likely to adopt the innovation than those who are isolated, because of increased interactions with those who have already adopted" (Greenan, 2015:147). This is a principle that has been commonly expressed in deterrence-based gang responses, and in particular, the claims of FBI officials in their targeting of gang leaders and highly involved members of the Lynn street gangs.

Formally, the Model for the Simultaneous Diffusion of an Innovation and Evolution of a Dynamic Network focuses on the adoption of innovation modeled as a time dependent binary

variable conceived in an absorption state $\{1\}$ indicated by random variable $Z_i(t)$ and when the time of adoption at t_i has been observed, then $Z_i(t) = 1$ if and only if $t > T_i$ (Greenan, 2015: 3). Over multiple observation points, *an adoption process* is established, which reflects the conceptualization "that social actors may adopt an innovation due to prior adoptions by those around them, due to a tendency to behave to one's peers" and where selection is defined as the preference of actors to instigate and maintain relations with whom they respect (Greenan, et al., 2015: 148). This adoption process is useful for accessing behavioral change as it is restricted in the sense that in cannot increase or decrease over time. Instead, it has one state, observed or not observed, dependent upon a vector of time discrete indicators such that the time parameters; $Z_t = (Z_1(t), \dots, Z_n)$ form the adoption process.

The objective function for behavior departs from the multinomial logit form as the adoption of behavior becomes a function of a proportional hazards model (Greenan, 2015). The proportional hazards model is concerned solely with establishing the base rate of infection, or rather *it is model bound to the rate at which actors transition to the adoption of a new behavior;* conforming analytically to a Cox (1973) regression and event history model (Greenan, 2015; Allison, 1999). As the binary dependent behavior diffuses through the network from 'early adopters', the Cox regression model establishes a baseline hazard from which "functions of the adoption process, the network, or any other measured actor attribute" become the focus of the model (Greenan, 2015: 6). This facilitates "the property that if a covariate is increased by some predetermined unit, then the effect on the hazard is multiplicative", and the hazards between actors based on a covariate such as gender can be easily compared (Greenan, 2015:6).

As a result of the hazard function, the only behavioral dynamics entering the diffusion model concern 'effects' that condition the base rate function and not the objective function

(Steglich et al., 2010). This is the case because of a restriction required by the estimation process: the rates of network and adoptions must be constant between observations consistent with a piecewise constant exponential model (Greenan, 2015, citing Blossfeld, 2002). Consequently, the diffusion model consists of a sole network objective function and a behavior hazard rate function. The objective network function takes the form:

$$fi(\gamma;\theta) = \sum_{k=1}^{K^{[X]}} \beta_k Si_k(y)$$

where $\beta_1, \ldots, \beta_k$ are parameters to be estimated and Si_k are effects that include outdegree, reciprocity, transitive ties, actor covariates and the dependent adoption variable (Greenan, 2015).

Through this function, Greenan (2015) was able to evaluate the impact of a behavioral innovation—smoking marijuana—on the coevolution of a friendship network with basic structural effects and the behavioral effects of alter, ego, and similarity. As previously described, alter and ego effects can be used to access whether actors became more popular or more social as a result of a behavior while the similarity effect examines the likelihood of ties to form between actors who have adopted (Greenan, 2015).[20] When these effects are included in the objective rate function of the SAOM, they act as controls for one another in modeling the dynamics of the social network as it evolves with the diffusion of innovation (Schaeffer, 2017; Greenan, 2015). Based on prior research, Greenan (2015) suspected that friendship ties would be more likely among juveniles who shared in their adoption of smoking marijuana, which was confirmed through a significant similarity measure, and insignificant alter and ego measures.

[20] It should be noted that the alter, ego, and similarity effects are formally evaluated at the dyadic level.

In the current study, the formulaic decomposition of the objective function will mirror Greenan's (2015) by including basic structural elements, actor covariates, and the alter, ego and similarity effects.[21] However, the alter, ego and similarity effects will be interpreted differently in the study because of the nature of the behavior being evaluated in the Lynn gang networks. In Lynn, the FBI's targeting of gang leaders was connected to two goals: preventing gang offenses through mechanisms of incarceration and specific deterrence among the targeted, and extending that prevention through the general deterrence mechanism among the untargeted. In the context of a behavioral change stemming from the efforts of law enforcement as change agents and the punishment effects of sanctions and threats of punishment: network dynamics in this study will reflect patterns of behavioral adoption, as opposed to the agency of actors.

For instance, it is not expected that the network dynamics of Lynn gangs would reflect that a gang member's popularity or sociality had increased as a result of their desistance decision in response to sanctions and threats. Nor would it be the case that gang members in Lynn would prefer to create ties with those who had desisted in the traditional sense of the similarity effect. Instead, the alter, ego, and similarity effects serve as controls in this study to indicate whether actors who desisted had more incoming or outgoing ties, and whether actors came to share ties in the network based on their desistance over the course of the FBI's enforcement efforts. In the later effect, similarity serves to proxy a general deterrence mechanism that if effective, would result in many gang members sharing ties with the behavior.

Additionally, it is believed that the structure of the study's network data will influence the interpretation of these effects. The strategy's sampling design was implemented to identify social connections between targeted and untargeted gang members in order to trace the impact of

[21] Structural and actor covariates are discussed in detail in subsequent chapters.

sanctions as well as the effects of risk communicated from opinion leaders to others in the gang network. In order to reflect this process, the study's network data is structured from the ego-centered networks of targeted gang members. In light of this structure, the effect of ego in the diffusion models should reflect this population as those with the highest number of outgoing ties in the network. In this way, the ego effect controlling for the other network dynamic effects will provide indications of incarceration and specific deterrence effects derived over the course of the enforcement campaign among targeted actors.[22]

With respect to the hazard function for the diffusion model, this takes the form:

$$h_i(t; y, \theta) = h_0(t) \exp\left\{\sum_{k=1}^{k} \propto_k a_{ik}(y)\right\},$$

where the time-dependent explanatory variables $a_{i1}(y), \dots, a_{ik}(y)$ are based on the current process state of $y = y(t)\ with\ \propto_1, \dots, \propto_k$ to be estimated from "functions of the adoption process, the network, or any other measured actor attribute" (Greenan, 2015:151). Effects are distinguished in the model between intrinsic characteristics—those that may affect the actors' propensity to adopt behavior irrespective of network adoptions—and a series of social proximity measures that model the contagion process (Greenan, 2015).

As a function of coevolution model's longitudinal framework, observed changes in behavior establish the base rate hazard while intrinsic characteristics identify differences between two actors hazard specific to an explanatory variable such as gender (Greenan, 2015). In Greenan's (2015) study, the inclusion of gender and the frequency of self-reported alcohol use revealed no differences in risk for females, but a significant increase in the hazard risk among

[22] The actor covariates and structural measures included in the study's objective network rate function are discussed in the data and measures, and analysis chapters.

those who drank more frequently. In this study as well, gender was included in the objective rate function to determine its' influence on network dynamics and the formation of friendship ties (Greenan, 2015).

This highlights a subtly of the model as actor attributes as well as statistics of the network such as outdegree can be used simultaneously to evaluate distinct effects through both the objective and hazard rate functions (Greenan, 2015). In the current study, this distinction enables the analysis of deterrence in a network comprised of cooffending relations through the objective rate function, and the ego, alter, and similarity effects, while the hazard function simultaneously evaluates risk of adoption through the communication flow relational structure. To further this distinction, the hazard function is where the effectiveness of the FBI's enforcement efforts is evaluated as a function of both direct sanctions and communication of punishment risk under the diffusion framework.

In terms of diffusion, the series of social proximity measures that trace behavior in the hazard rate are first provided in a 'closeness' measure:

$$a_{ik}(y) = \sum_{j=1}^{n} z_j d_{ijk}(y)$$

where $d_{ijk}(y)$ is a measure of closeness between actors $i \ and \ j$ and the indicators $\{z_{1 \dots} z_n\}$ note that the effect sums over only those j which have adopted the innovation. This measure was modified by Greenan (2015) so that it generalized to the total amount of potential influence that adopters have on actors for whom they are tied. This is also referred to as an infection measure that restricts adoption effects to situations where there is a tie from ego to alter:

$$a_{i1}(y) = \sum_{j=1}^{n} z_j \, x_{ij} s_j(y)$$

where x_{ij} can also be interacted $s_j(y)$ to reflect infection by indegree, outdegree or a time-independent attribute such as gender (Greenan, 2015).

An exposure modification is also used in the hazard to evaluate "social influence conveyed through [the] overt transmission of information" where positive coefficients indicate "that being tied to adopters increases the chances of adopting" (Greenan, 2015:153). Exposure is captured by a proportional and a total exposure measure given respectively as,

$$a_{i2}(y) = \frac{\sum_{j=1}^{n} z_j \, x_{ij}}{\sum_{j=1}^{n} z_j x_{ij}}$$

$$a_{i3}(y) = \sum_{j=1}^{n} z_j \, x_{ij}.$$

where influence is accessed based on the proportion of contacts adopting or the total number of contacts (Greenan, 2015).

The last contagion effects concern the actor's susceptibility to total exposure:

$$a_{i4}(y) = p_i(y) \sum_{j=1}^{n} z_j \, x_{ij}$$

and a susceptibility to average exposure measure (Greenan, 2015):

$$a_{i5}(y) = p_i(y) \frac{\sum_{j=1}^{n} z_j x_{ij}}{\sum_{j=1}^{n} x_{ij}}$$

These measures are intended to answer whether "adoptions affect only those from whom the adopter has a tie" (Greenan, 2015:154). The total exposure measure for susceptibility can also be

interacted with outdegree to access whether more active actors saw increased risk of adoption (Greenan, 2015).

In the current study, these measures are used to evaluate the impact of the FBI's enforcement actions against the Lynn gangs consistent with the diffusion framework and testing the study's hypotheses. Actor covariates traditionally associated with offender differences will be used within the objective and hazard rate functions to access their respective effects on network dynamics and the hazard of adoption. A covariate specific to this study similarly evaluates distinctions in hazard based on the targeted status of the actor. Conceptually, the FBI's use of Enterprise Theory of Investigation and structured prosecution enforcement approach is consistent with the intention to raise objective risk levels relative to punishment severity. In this study, the average sentence length for federally targeted actors was found to be 8.4 years versus 1.2 for state charged actors.[23] Federal targets were also relocated to other areas of the country at the discretion of the Federal Bureau of Prisons, and were ineligible for sentence reductions that were otherwise available to state targets. The interaction of this measure with the hazard through social proximity measures will facilitate the study of severity differences as a function of risk through the network of ties. In the next chapter, the study site is reviewed briefly, while study data, and measures are described in more detail. This chapter also emphasizes the sampling procedures used to establish the type of data required to implement the diffusion of innovation analysis.

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[23] It should be noted that sentence length data on gang members convicted federally was obtained through the public portal for the Federal Board of Prisons "Inmate Locator".

STUDY SITE, DATA AND STUDY MEASURES

In the City of Lynn, the rise of organized national street gangs resulted in waves of retaliatory street violence, and when local enforcement efforts failed to impact the problem, assistance was sought from the FBI under the Safe Streets Gang Initiative. In 2006, the FBI activated their Enterprise Theory of Investigation against the groups responsible, and through a series of enforcement efforts that extended into early 2013, officials claimed that they had effectively dismantled the groups by sending a strong deterrent message. With those claims yet to be examined, the current study uses the diffusion of innovation model to evaluate the effectiveness of the FBI's sanction-based enforcement efforts within the groups that were targeted by the FBI. The reconceptualization of deterrence theory in a networked diffusion framework is also intended to evaluate the marginal deterrence hypothesis and the question of whether sanctions impacted perceptions of risk as evidenced by the behavior of the Lynn street gang members.

This approach is made possible by a unique data set that combines actor attributes with social network relations. This data leads to the identification of the communication flow relations from which information on risk travels through the gang network structure, and enables the assessment of risk on behavior for those connected to the gang members that were targeted. This data originated with a 'multisystem' criminal network approach combining information from police surveillance, experiential police data, and official police and criminal history records (Malm and Bichler, 2011). The multisystem approach has been used in criminal network research to address the issue of network boundary, and to strengthen the validity of study findings. Police surveillance data is "collected through the course of an investigation…[and] generated from objective communication rather than police perceptions" (Morselli and Roy, 2008:277). This information establishes roles and connections based on the unbiased

interactions between the criminal actors themselves. Experiential police data provides a source of grounded information on criminal networks gained from law enforcement knowledge on individuals and their associations (Malm and Bichler, 2011). This knowledge often negates false perceptions concerning network boundaries because of the understanding investigators have established through their interactions with criminal groups (Malm and Bichler, 2011).[24] The third source of network information, police crime data, is generated from official incident and arrest reports, and it locates criminal relationships between individuals from formal encounters with police officials (Malm and Bichler, 2011).

In this study, surveillance data was obtained through the investigation files maintained by the Lynn Police Department in connection with the FBI operations. These files detail the enterprise activities of individuals associated with the violent street gangs in Lynn and contain standardized reporting documentation that captured the purchase and sales of narcotics and firearms involving cooperating witnesses. In addition, surveillance logs documented contacts between targeted gang members and other individuals in a variety of circumstances including reported and unreported incidents of violence and formal gang meetings where FBI informants recorded gang member interaction. In terms of surveillance data, the information was more extensively captured in Operation Melting Pot given that it was the largest of the FBI operations. The data extracted from these files include information on dates of contact, person or persons involved, and the type of activity arranged or completed. Experiential police data filled in the gaps in terms of the surveillance data. The author was uniquely positioned to access the members of the Lynn Police Gang Unit directly involved with the FBI throughout the

[24] This knowledge has also been used in developing new understandings of street gang violence and guiding street gang response (Braga, et al., 2000).

operation.[25] These officers confirmed target identities who did not appear in files and they were also able to illuminate the boundaries of the gang network consistent with their experiences with the groups.

Surveillance and experiential data provided for the study's sampling strategy in conjunction with the police crime and FIO reports of the Lynn Police Department. An adaptive sampling design—analogous to a snowball strategy—was used to derive network information from a seed population of targeted actors. Subsequent sampling was conducted from targeted actors based on the presence of associational ties documented in the crime and FIO reports. These field interrogation reports (FIO's) documented encounters that resulted in no arrest or no formal reports of crime, but which contained information on targeted actors and their associates. An association in this study was defined for actors who had at least two documented interactions.

This type of adaptive sampling design in network research is used to identify hidden populations, and in the current study, it similarly identified a population of untargeted, networked individuals that would be affected by changes in objective risk.[26] Sampling was conducted for the period from 2004 to 2018, which produced a study population of N=550 actors with N=69 federal and N=45 state targeted actors. While press releases indicated that 158 individuals were targeted by the FBI, an analysis revealed that many listed were never charged. These individuals were confirmed to be informants by police officials and as such were excluded from the study as their identities were well known among street gang members through subsequent court proceedings. However, the adaptive sampling strategy identified eighteen individuals that were targeted by the FBI who were not located in press releases, experiential, or

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[25] The author was employed by the Lynn Police Department before, during and after these operations.
[26] See Giles and Hancock (2007) for more information on the adaptive sampling design for social networks.

surveillance data. These 18 individuals resulted in the addition of twenty-four untargeted network members to the study's network data.

In addition to their role in network identification, crime report files provided data on gang affiliation, age, race and year of contact. The gang affiliations listed in these records were largely a product of either self-nomination or a nomination process where police investigators:

> Would ask [informants] if they knew specific information about the hierarchy of the gangs, who their gang membership included, as well as…[who were their] associates. We would also take that information that they gave us and try to corroborate it through means of intelligence [through] other local law enforcement [sources and other] agencies. (*Comm v. Cabrera*, 2011)[27]

Criminal Offender Record Information (CORI) data was obtained for the study population from the Massachusetts Criminal History Systems Board. Data on race, age, social ties and offending history were collected for the period 2004 to 2018, the year preceding the Lynn intervention and five years following its conclusion.[28]

STUDY MEASURES

In this study, actor covariates of race, age, and prior offending are evaluated through a series of rate measures that access their role on the tie preferences of gang members in Lynn. These 'RateX' measures are evaluated in the objective function of the diffusion model, and are indicate in the table below. The race measure included the following categories: white, black, Asian and Hispanic, while measures of age and prior offending were converted from an original

[27] Testimony of Detective Steven Withrow. This researcher was also able to consult with gang validation forms completed by the Essex County Correctional Facility as part of their intake process for selected individuals (N=28). The recorded affiliations in these records aligned with those found in surveillance files or crime report data.
[28] Data from the Lynn Police Department and the Massachusetts Criminal History Systems Board was authorized through formal researcher agreements. This study was reviewed and approved by Northeastern University's Institutional Review Board (IRB) with all participants in the study deidentified to protect confidentiality. The opinions expressed are those of the author and do not represent the views of the Lynn Police Department, Massachusetts Criminal History Systems Board or Northeastern University.

count to an ordinal scale variable (1-5). These changes were made due to an internal statistical constraint in the Stochastic Actor Oriented Model where ordinal variables are recommended to be restricted to 5 levels of measurement (Ripley, et al., 2018).

The attribute of race and its network dynamic effect is of particular interest in this study because of the representations made by law enforcement officials that Lynn gangs were uniquely multi-racial. The belief was so persuasive that it influenced the naming of the FBI's second and largest Lynn intervention, Operation Melting Pot. Prior research on gangs however, has indicated that street gang violence is patterned by high levels of racial clustering, and that race is probably one of the most important influences in the creation of ties (Papachristos, Braga, and Hureau, 2013).[29] In this study, the race measure evaluates whether race did in fact play a role in gang member decisions to create ties in the Lynn gang networks. The actor attributes of age and prior offending similarly access whether decisions to create ties were influenced by the age or offending histories of members in the Lynn gang network.

The dynamic effects of behavior on network structure in the objective function are conveyed through ego, alter and similarity effects related to the adoption of desistance. These effects are based on a dichotomous offending measure reverse coded 1 to indicate targeted gang actors who did not reoffend after sanctioning, and to indicate untargeted members who did not offend subsequent to their entry into the network. Offending histories were used to construct this dichotomous dependent variable, and included any recorded Uniform Crime Report Part I offenses, and violations of Massachusetts criminal codes related to drug distribution. The standard Part I offenses in this measure are homicide, non-negligent homicide, aggravated

[29] This study used a social network-based Exponential Random Graph Model to study instances of violence between gangs in the cities of Chicago and Boston. Gangs in both cities exhibited strong signs of racial clustering.

assault, and robbery. The coding of the desistance variable is consistent with the requirements of the diffusion model in restricting the effects of the behavior to the objective rate function for network dynamics and in facilitating the tracing of desistance adoption through the hazard rate function.

In this hazard function, actor attribute measures, network statistics and social ties are evaluated for their impact on the risk of desistance adoption by Lynn gang members. The study's null hypothesis related to offending behavior change is accessed through a targeted-gang member attribute measure coded 0, 1, and 2 for untargeted, state, and federally charged actors, respectively. Additionally, the previously described attributes of prior offending, age and race are used in the hazard to evaluate whether risk of adoption was conditioned by the individual's criminal history, their age or by their race. As a reminder, actor attributes that enter into the hazard model reflect contributions to risk irrespective of the social tie connections in the Lynn gang network.

For the role of ties, the hazard function is used in conjunction with social contagion measures to evaluate the hypotheses related to communication and perception of risk. In this study, the effects of average and total exposure evaluate the impact of a gang member being connected to another who desisted from offending based on the proportion or total number of contacts who had adopted. These measures relate to the overt transmission of risk conveyed through the desistance of other gang members with whom the individual gang member was connected. Infection measures are used in this study in interaction with the gang target measure and the network statistic of outdegree. These measures access directly whether actors tied to federal or state charged gang members saw higher hazard rates or whether actors tied to more active gang members in the network saw higher risk. In particular, these infection measures are

intended to proxy the connection between objective risk, perception, and behavior as reflected in their effect on the hazard of adoption. The final contagion measures in this study concern susceptibility measures that are interacted with the actor attributes in the study. These measures attempt to identify how responsive gang members in the network were to the adoption of their gang contacts conditioned by age, race, criminal history, or whether there was an enhancement in risk for targeted gang members being connected to other FBI targets. The final effect included in this study's hazard model is the network statistic of outdegree. This effect is used to evaluate whether more active gang members in the Lynn network had higher risks arising from their increased interactions to other gang actors in the network

Figure 8: Network Measures Evaluated in the Diffusion Model

Variable Name	Description	Measurement Type	Interaction
RateX (Network)	effect Race on rate	Rate	Race
RateX (Network)	effect Target on rate	Rate	Target
RateX (Network)	effect Gang_ID on rate	Rate	Gang_ID
RateX (Network)	effect Prior_off on rate	Rate	Prior_off
RateX (Network)	effect Age on rate	Rate	Age
RateX (Network)	effect my_beh on rate	Rate	my_beh
my_beh	outdegree effect on rate my_beh indegree effect on rate my_beh average exposure effect on rate my_beh	Rate Rate Rate	mynet mynet mynet
my_beh	effect Race on rate my_beh effect Target on rate my_beh effect Prior_off on rate my_beh effect Age on rate my_beh	RateX RateX RateX RateX	Race Target Prior_off Age
my_beh	susceptibility to av. exp. by Race effect on rate my_beh susceptibility to av. exp. by Target effect on rate my_beh susceptibility to av. exp. by Prior_off effect on rate my_beh susceptibility to av. exp. by Age effect on rate my_beh	susceptAvCovar susceptAvCovar susceptAvCovar susceptAvCovar	Mynet X Race Mynet X Target Mynet X Pri_off Mynet X Age

It is important to note that the model building procedure for a Stochastic Actor Oriented Model is based on the use of an iterative approach designed to address the issue of collinearity with model effects (Ripley, et al, 2015). Because of the dependency assumptions of the model, levels of collinearity are expected, but in cases where two effects are closely related, they are often dropped. In the case of the diffusion of innovation model and the contagion effects noted above, Greenan (2015) had to drop several susceptibility measures from her models, and it is possible this will apply in this research. The current study's diffusion model will report results derived from six waves of data structured purposely to enable the tracing of desistance through the network at the timepoints in which the actors in each operation were targeted and arrested by the FBI. Upon entry, targeted actors bring their relational ties with them, facilitating the flow relation structure from which communication of risk would travel to impact perception and subsequent offending decisions (see Figure 7). All social network analyses begin with the descriptive analysis and reporting of key actor attribute data and network statistics. In the next section, these are provided for the Lynn gang network at the end of the study period.

LYNN ACTORS AND THE GANG NETWORK (DESCRIPTIVE)

Descriptive network models are a standard in social network studies "used to visualize networks… describe specific characteristics of overall network structure as well as [provide] details about individual nodes, ties and subgroups within the networks (Luke, 2015: 3). Table 1 below provides the race of study participants, and contains a breakdown of targets by race. Black (34%) as well as Hispanic participants (34%) constituted the largest population groups while whites constituted the smallest (10%). Nearly 21% of the population is of Asian descent and out of 550 study subjects, only 18 are female. In the breakdown of federal and state targets

by race, a Pearson's Chi-squared test indicated that there was no correlation between actor race and status as either a federal or state target (p =.84). Table 2 presents additional information on population age and offending, followed by a boxplot reporting the offending distribution for study participants that indicates slightly higher means for black subjects and a number of outlying scores in each race.

Table 1:: N=550 Actors by Race and Target Status

	Asian	Black	Hispanic	White
Race	114	190	188	58
Federal	13	28	24	4
State	9	16	15	5

	Age	Offending History
Minimum	12	0
Mean	22.76	22.34
Max	54	147

Table 2: Minimum, Mean and Max (Age and Offending)

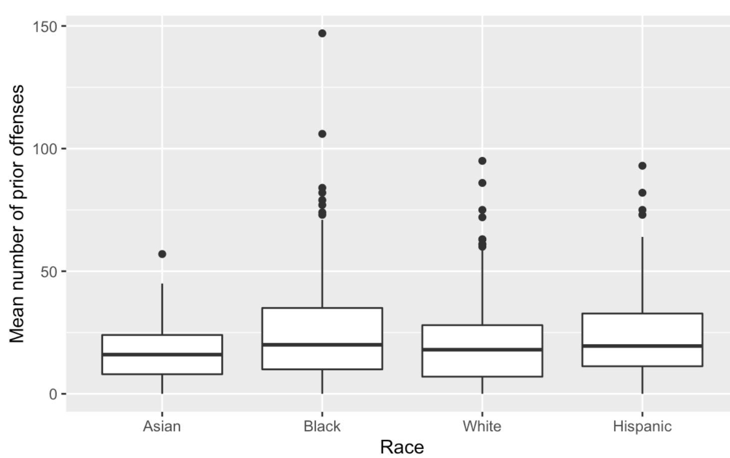

Figure 9: Boxplot of Mean Offenses by Race (N=550)

Standard descriptive measures for the network are reported in Table 3. These measures identify the size of the social network, its' density, its' diameter, the number of distinct subgroups, and the average number of ties for network members. The size of a network is the

most general statistic and indicates how many vertices and edges are present in the sociomatrix. In the directed network of Lynn gangs over the course of the study periods, this reflects in a large network size of 4,482.

Network Size	4482
Network Density	0.029
Diameter	12
Clusters	113
Clustering Coefficient (average)	0.32

Table 3: Lynn Gang Network Descriptive Variables

Network density is a measure connected to a restriction that networks can only have as many ties as it has nodes provided in the general formula $\frac{2L}{k \times (k-1)}$ where L is the number of observed ties and K the number of network actors. Density is a ratio figure with a range of 0-1 that is typically used to make comparisons with the clustering coefficient, and in more general comparisons with other networks. The reported density of .02 indicates that 2% of possible ties were observed. Network diameter reflects a path distance measure that identifies the maximum number of paths between the two most distant actors in the network. Diameter is an inference for determining how easy or difficult it is for information to travel through a network. In large scale, geographically-based diffusion campaigns, it is often connected to a death of distance phenomenon that restricts diffusion (Graevenitz, Graham and Myers, 2019). The diameter of 12 reported for the Lynn gang network in Table 3 is considered large (Moldovan, et al., 2016).

In this study, the inference of diameter relates to a network clustering effect described by the FBI, which involved the operation of sub-groups within the targeted network, and whose sales of drugs and firearms cut across the landscape of gang conflict and rivalries.[30] The clusters

[30] Affidavit of S.A. Jeffrey Wood (2010): p.3. These smaller groups are illustrated in figure 11 below.

measure reported is based on the maximally completed subgraphs observed in the overall network, which technically consists of the presence of all available ties in network subgroups called cliques. There are a large number of clusters in the Lynn gang network reported in Table 3. The clustering coefficient in the table is based on the average density within clusters, and as reported, a coefficient of .32 is considered moderately high (Malm and Bichler, 2011).

An important issue of first impression concerns the structural location of gang members targeted at the federal or state level by the North Shore Gang Task Force. Officials claimed that these individuals occupied leadership roles or played key roles in incidences of violence and directing gang activity. In network terms, these types of offenders should function in the network role of cut-points or bridges (Hage and Harary, 1983; Granovetter, 1973). Actors in this role provide the only linkage between two points in a network structure (Hage and Harary, 1983). Typically, network research has focused on cutpoints from a network disruption perspective whose removal would…[result]…into two or more separate subsets between which" there would no longer be connection between the subsets (Scott, 2001: 107). In Figure 10, actor 1 is depicted in the classic conception of a cut-point or weak bridge whose removal would dissect actors 3, 4, and 5 from the others in the network. Actor 7 is also a weak bridge. Alternatively,

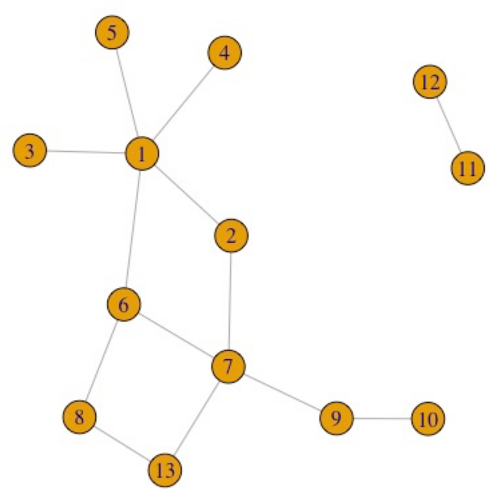

Figure 10: Depiction of Weak Ties and Bridges

actor 2 is a bridge actor that serves to link two clusters ideally positioned for directing or providing information in the network.

The importance of bridge actors in gang-based deterrence efforts rests with the connection between the targeting of gang leaders and their role as opinion leaders. From the law enforcement perspective, gang leaders and highly active gang members are targeted precisely because they may occupy these positions.[31] In the figure below, the Igraph package in the R

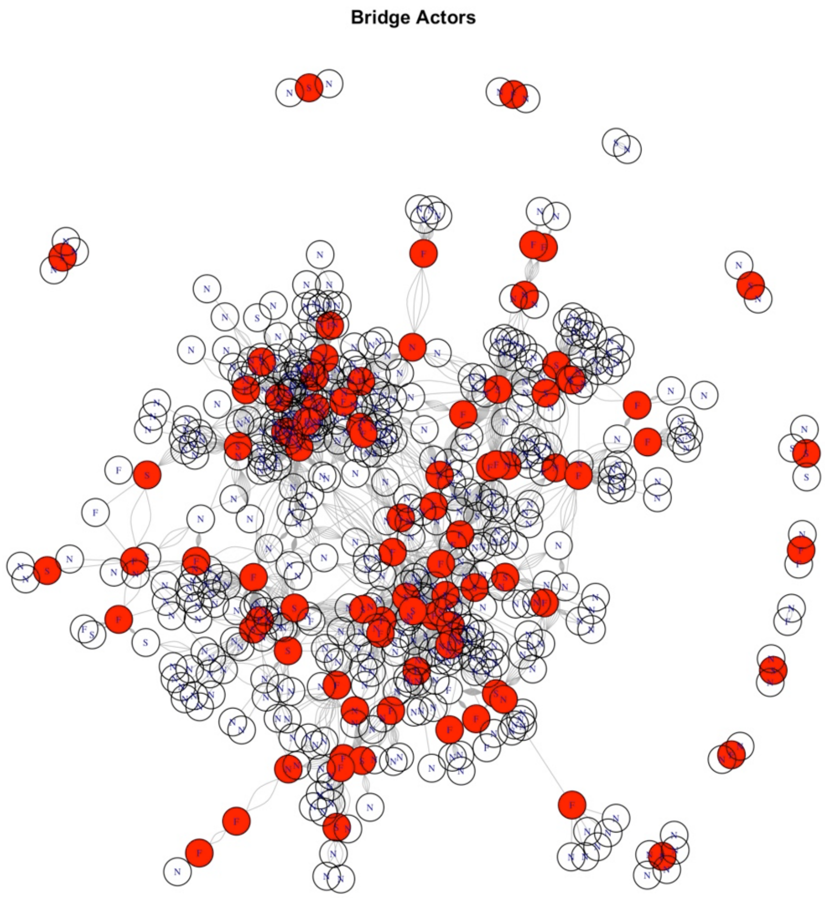

Figure 11: Bridge Actors in the Lynn Gang Network

[31] The bridge or cutpoint actor has featured centrally in criminal network and gang studies. For example, Malm and Bichler (2011) positioned that the removal of bridge actors in illicit criminal networks would impact group offending by reducing network redundancy between clusters. Similarly, McGloin (2005) discussed these actors as cutpoints whose removal would impede the opportunity for gang members to continue in committing organized group-based offenses. Yet others have related the principle to an actor's embeddedness in the structure of gangs or criminal networks (Vargas, 2014; Pyrooz, et al., 2013).

statistical software suite was used to identify the bridge actors in the Lynn gang network based upon a betweeness centrality measure that "captures a person's role in allowing information to pass from one part of the network to the other" (Golbeck, 2015:229). In criminal network research, betweeness centrality has been thought to produce "a more quality-based set of contacts [that indicate the] centrally positioned as key intermediaries or brokers within [a criminal] network" (Morselli, 2009). The individuals who were in these roles and positions are indicated in the graph as the red colored nodes. An overlay was also applied to identify gang actors on the basis of their targeted status (federal, state, untargeted). As this figure indicates, the majority of the state and federal targeted gang members occupied bridge positions within the Lynn network linking both individuals, and clusters of individuals. Accordingly, targeted gang members would have been in positions favorable to communicating information on risk within the network structure.

CHAPTER 4

MODEL DEVELOPMENT AND ANALYTIC FINDINGS

As outlined, this study applies social network analysis to understand the communication of deterrence within the gang networks in Lynn, Massachusetts. To accomplish this, an analytic strategy employing a Stochastic Actor Oriented Model is used to examine the connections between sanctions, risk and perception. The models for this study were developed using the Simulation Investigation for Empirical Network Analysis (SIENA) package within the R Statistical software suite. SIENA is a set of statistical tools designed to implement the Stochastic Actor Oriented Model in the study of the coevolution of network and behavior. As such, these models make predictions concerning network or behavior through a stochastic algorithm and Methods of Moments estimator, which as part of the Markov process, models "the total change[in network and behavior]…through simulations of small, unobserved changes that are assumed to accumulate to create that total change" (Ragan, et al., 2019). For this study, this process leads to network predictions that are based on the cooffending ties of Lynn gang members collected over the course of the 13 year study period. Predictions concerning behavior are similarly based on adoption decisions during the period after specific gang leaders were targeted, while predictions of untargeted gang member behavior are based on decisions subsequent to their entry with the leader with whom they were tied.

As described in Chapter 3, SAOM models are built out using an iterative process, which in SIENA connects to collinearity concerns as well as model convergence. Convergence in SIENA models is deemed adequate with included effects when T-statistics for deviation from target is no larger than .1, and the overall model convergence is less than .25. T-statistics reflect problems with effect collinearity and those above .8 are often dropped from the model. In

instances where the overall model convergence does not meet these thresholds, the estimation is repeated with prior values as a starting point for estimation (Ripley, et al., 2018).

It is also noteworthy that SIENA models do not report an overall measure of statistical significance as in the case of r^2 in linear regression models. Rather, t-values are used to establish significance based on the z-scores for each parameter calculated by dividing the estimate by its standard error. Another recommendation in SIENA modeling is researcher consultation with the Jaccard Index. The index is a measure of observed network change between study periods, which is related to the initiation and proper implementation of the Markov process. This index alerts researchers to problems of network inertia that may make the model an inappropriate analytic choice. The threshold for the Jaccard Index is .30; however, indexes as low as .20 are tolerated (Ripley, et al., 2018). Lastly, in the estimation of these models, published results are recommended to be based on 3,000 calculations of the covariance matrix in phase 3 of the estimation process (Ripley, et al., 2018). All models in this study were based on 6,000 calculations.

In this study, models reported were quite robust in terms of T-statistics and overall model convergence; however, several measures had to be dropped from the analysis because of collinearity issues, and model convergence problems. The Jaccard Index across the reported models was .24 for the first wave period and ranged between .47 and .86 for the other waves. It is important to note that the first wave of the study's data was required to initiate the Markov process, and therefore, there are five periods reported in the model results.

An issue particular to this research relates to the way in which SIENA accommodates the structure of the study's network data. SIENA models typically report a measure of network density based on the average outdegree of network actors, which functions analogously to the

intercept reported in regression models (Schaefer, 2017). While the density is not interpreted, its' intercept function connects to the creation, maintenance, and dissolution of ties predicted to take place in the network. In the current study where the data is structured from the entry of actors across waves, the only network change that occurs in the network reflects the addition of ties. By design, SIENA identifies this type of data structure as an 'up only' network, which results in the intercept measure not being reported. Consequently, in the analysis of the cooffending ties, actor decisions will reflect the addition or maintenance of ties. All models in the study included the required structural effects of reciprocity, a form of triadic closure, alter, ego, and similarity effects, and actor covariates. The first study model was designed to evaluate the network structure of the Lynn network and the study's null hypothesis pertaining to offending change among targeted actors. It also examines the communication-based hypothesis related to the transmission of risk; measured through the average and total exposure effect measures noted previously. The results from this model are reported in Table 4.

The mean network change opportunities and baseline adoption hazards reported reflect the average number of opportunities a gang member had to make a tie change or to change behavior. These model statistics are typically reported in network models, but they are otherwise not a focus of researchers as they are restricted to the specific network, and the majority of research interest is in the direction of change captured by the objective model functions (Ripley, et al., 2018; Schaeffer, 2017). Nonetheless, the baseline, period adoption hazards reported are noteworthy in this research as the period hazards reflect change in actor opportunity to desist from crime largely driven by the FBI's targeting of gang members within the Lynn network. Illustratively, fluctuations in the baseline hazard follow the pattern of FBI responses to street gangs in Lynn. The hazard period at wave 5 (1.98) is an indication of the cumulative change

opportunity for gang members in the network to change behavior at the end of the FBI's enforcement efforts effects. The reciprocity effect reported is a dyadic measure that captures the tendency to reciprocate and maintain ties. In friendship networks, the average reciprocity estimate is 1.97; however here at 5.06, the measure indicates a very strong preference among gang members to maintain and reciprocate their cooffending ties (Schaeffer, 2017). What is remarkable is that these relations endured through periods of gang conflict and violence, as well as the concerted efforts of the North Shore Gang Task Force to dismantle the targeted groups.

	Estimate	*Std. error*	*t*
Network Dynamics			
Mean change opportunities (period 1	0.44	(0.02)	
Mean change opportunities (period 2)	0.64	(0.03)	
Mean change opportunities (period 3)	0.35	(0.02)	
Mean change opportunities (period 4)	0.23	(0.02)	
Mean change opportunities (period 5)	0.29	(0.02)	
Effect of Race**	.11	(.02)	5.50
Effect of Age**	-.24	(.02)	4.80
Reciprocity**	5.06	.15	33.73
3-cycles**	2.46	.38	6.47
Behavior alter	.06	.08	
Behavior ego**	10.3	.85	12.11
Behavior similarity	-.21	.11	
Number of Alters at Distance 2*	-.02	.01	2.00
Adoption Effects			
Integrated baseline hazard (period 1)	0.56	(0.05)	
Integrated baseline hazard (period 2)	0.25	(0.04)	
Integrated baseline hazard (period 3)	0.81	(0.09)	
Integrated baseline hazard (period 4)	0.51	(0.08)	
Integrated baseline hazard (period 5)	1.98	(0.23)	
Outdegree*	0.10	(0.05)	2.29
Total exposure*	-0.20	(0.08)	2.72
Average exposure	0.24	(0.29)	
Target*	0.18	(0.08)	2.25
† $p < 0.05$* † $p < 0.01$** All t ratios < .1 *Convergence: .11*			

Table 4: Model 1

The triadic measures selected for this study—3-cycles and Number of Alters at Distance 2—were chosen because they relate to the role of trust and exchange in the decision to forge ties (Contractor and Forbush, 2017; Morselli, 2009). Such decisions have been found in criminal organizations or cartels to reflect "norms of reciprocity and equity" that portend benefits for the individual in establishing and maintaining network ties (Contractor and Forbush, 2017:16). In the Lynn gang network member ties, these norms as well as the importance of trust were evidenced by the large effect size reported for reciprocity. In a networked perspective of exchange, trust is extended in the triadic structure to reflect expected returns on the part of the individual in the creation of ties (Contractor and Forbush, 2017). This is illustrated below in the 3-cycle figure, which captures exchange based on a friend of a friend phenomenon found to

significantly operate in the tie structure of the Lynn gangs. In this case, exchange involves the case where gang member (i) establishes a relationship with gang member (j) because of the existing relationships between gang member $(j), (h)$ and $(h), (i)$ (Ripley, et al., 2018). This effect formalizes trust as a function of exchange whereby gang member (i) realizes a benefit the same as would gang member (j) from closing the triad. The 3-cycle effect was significant and extends the importance of trust and exchange previously found in criminal offending groups to the Lynn gang network (Morselli, 2009). The Number of Alters at Distance 2 measure adds another dimension to exchange as the negative and significant value indicates that the gang member (j) would attract a tie only in cases where that individual had many connections in the network (Ripley, et al., 2018). In this way, gang members forged ties through the friend of a friend phenomenon because of the desire or value of being connected to more active gang members.

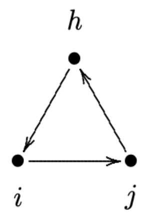

Figure 12: 3-cycles

Based on effect sizes for reciprocity and 3-cyles indicating an outsized influence of trust and exchange, no hierarchal structure was found in the ties between gang members, which negates inferences of central network control (Ripley, et al., 2018; Morselli, 2009). This directly contradicts the portrayal of the street gangs as organized criminal organizations claimed in official court affidavits and public statements by law enforcement officials (S.A. Jeffrey Wood, 2010; United States Attorney, District of Massachusetts, 2010). Instead, the structure of cooffending ties between gang members in Lynn appears to reflect how "gang membership is not a 'master status'…[and that] individual gang members often act on their own or in subgroups outside the gang" (Decker and Van Winkle, 1994:593). Morselli (2009:10) has previously noted how social network models go beyond the traditional boundaries of the group, and possess the capacity to grasp in cooffending settings, how offenders never actually meet despite their loose

associations with a criminal operation. In the cooffending ties of the Lynn gang network, this appears to be the case provided that nearly 60% of the study population were unaffiliated with a group under the gang member classification procedures previously described.

The influence of race was also evaluated in this study to examine claims made by police that Lynn gangs became more diverse because of the lifting of recruitment requirements by nationally-aligned street gangs. Race, consistent with previous studies was found to be a strong and significant predictor of ties between the gang members in Lynn (Charette and Papachristos, 2017; Papachristos, 2013). This disconfirmed the law enforcement narrative in finding that the social ties were homophilous on race. The influence of age, and the question of whether gang members preferred relations to similar aged individuals were found to be insignificant. This was somewhat surprising given the correlation between youth and street gang membership, and other network studies that have indicated evidence of age homophily in cooffending networks (Charette and Papachristos, 2017; Woods and Alleyne, 2010).[32]

In terms of the FBI's targeted enforcement strategy and the study's null hypothesis, the behavioral effects of similarity, ego, and alter reported in Table 4 indicate a network desistance pattern among the targeted, and most active gang members only. The ego effect which identified the behavior among the most active was highly significant (12.11) while desistance was not seen in the network patterns of popular gang members, nor was it observed in patterns of ties linking members by their shared adoption of desistance. Collectively, these effects indicate that the FBI's targeting of gang leaders had little effect outside of the population that was sanctioned. Indeed, if the effort has been successful in generating credible messages of punishment risk, the

[32]Prior offending was included in this model initially in order to access whether offenders preferred each other based on level of crime involvement. There was high collinearity with this effect and it was not significant. When dropped, convergence for the model improved from .23 to .11.

impact would have been seen in network patterns of shared behavior because of the positive behavioral responses of others in the gang network. Consistent with these findings, the claim connecting the North Shore Gang Task Force efforts to a broader deterrence effect among gang network members is contradicted while the study's null hypothesis is rejected in finding that sanctions against specific gang members had significant deterrent effects.

The hazard rate function also lends to a rejection of the null through a target measure that indicates that the gang members sanctioned by the FBI saw their the log-odds of adoption increase 1.19. The reported network statistic of outdegree in the hazard further indicates that a more active gang member in the network saw their risk of adoption increase 1.1, irrespective of whether they were targeted or not. In this respect, increased interaction with others in the network appeared to play some role in the adoption of desistance behavior.

In the Model 1 hazard, the effects of average and total exposure evaluated the question of whether gang members saw their risk for desistance increase as a result of their social tie connections to members who had desisted from offending. These effects therefore tested the proposed social tie-based linkage between objective risk, communication, and perception. As general measures, this risk was based on the proportion or total number of the gang member's contacts who had desisted. Both of these effects were insignificant, and indicate that the FBI's sanctions failed to elevate the perception of risk based on the communications that took place along all social ties in the network. While there was some average exposure effect found, the standard error for the measure indicated a good deal of variation between actors in their response to the threats that were communicated.

In the study's second model, the hypotheses related to punishment distinction and social contagion were tested. Punishment severity was evaluated by a dichotomous federal and state

targeted hazard measure, which distinguished gang members convicted of enterprise statute violations from those convicted of traditional state offenses. Federally convicted targets saw no statistically significant increase in their hazard, while state convicted gang members saw their hazard risk increase by 1.64. This finding contradicts the claims made by police officials. Enterprise enforcement is the lynchpin to a strategy that intends to deter gang offenders by punishing gang leaders more severely, yet those in Lynn who were targeted and convicted of enterprise violations failed to respond accordingly. But perhaps, those connected to them were impacted?

	Estimate	*Std. error*	*t*
Network Dynamics			
Mean change opportunities (period 1	0.44	(0.02)	
Mean change opportunities (period 2)	0.64	(0.03)	
Mean change opportunities (period 3)	0.35	(0.02)	
Mean change opportunities (period 4)	0.23	(0.02)	
Mean change opportunities (period 5)	0.29	(0.02)	
Effect of Race on Rate**	0.11	(0.02)	5.50
Reciprocity**	5.06	(0.15)	33.73
3-cycles**	2.45	(0.39)	6.47
Behavior alter	0.06	(0.08)	
Behavior ego**	10.3	(0.85)	12.11
Behavior similarity	-0.20	(0.10)	
Adoption Effects			
Integrated baseline hazard (period 1)	0.56	(0.05)	
Integrated baseline hazard (period 2)	0.25	(0.04)	
Integrated baseline hazard (period 3)	0.81	(0.09)	
Integrated baseline hazard (period 4)	0.51	(0.08)	
Integrated baseline hazard (period 5)	1.98	(0.23)	
Age on Rate**	-.21	(0.05)	4.20
Federal Target	0.08	(0.16)	
State target*	0.50	(0.18)	2.77
Infection by outdegree**	-0.02	(0.01)	4.61
Infection by Federal Target	0.13	(0.16)	
Infection by State Target	-0.33	(0.25)	
† p < 0.05* † p < 0.01** All t ratios < .1 *Convergence: .12*			

Table 5:Model 2

This was examined through the contagion measures of infection and susceptibility, and specifically Federal and State infection measures. These measures accessed the direct relationship between sanctions and threats of punishment from the targeted gang members to untargeted. In this case, being connected to either a state of federal targeted member was found to not increase the hazard for adoption. As the proxy measure evaluating the linkage between objective risk, communication, and perception, this study found once again that the members of the street gangs did not receive or respond to the message that was intended by the FBI's campaign. Further attempts were made to evaluate the average and total susceptibility

measures. These were described in the data and measures section; however similar to Greenan's (2015) experience, models that included these effects failed to converge and had to be dropped.

The final area examined in the second study model explored whether risk for desistance was conditioned by the gang member's age, race or prior offending. Race was found to be both highly correlated with the network period rates, and the objective function race effect and had to be dropped from the model.[33] Prior offending was highly correlated with outdegree, insignificant and dropped to improve model fit. The actor attribute of age retained in the model was negative and significant indicating that age did not increase the hazard risk for adoption. As a consequence, the overall results of the hazard model indicate that state charged gang members saw an increase in their risk of adoption, while those sanctioned more severely did not see an increased risk. Infection/contagion measures further indicate that being connected to targeted gang leaders did not increase risk, and that the actor attributes of age, race and offending history did not condition risk.

With social ties in this study conceptualized as conduits for risk information to travel, and the nexus between objective and perception placed at the interactional level with tie-based infection measures—the question was whether there were any non-network or network-based explanations that could assist in interpreting these findings. On one hand, the null effects for infection could indicate that the population of untargeted actors were unpersuaded by the FBI's sanctions or perhaps, untargeted actors increased their offending in response to the removal of those who were targeted. By examining the offending rates for each population, both appeared unlikely. Only 9 percent of the 436 untargeted network members offended in the study period; a

[33] This is an example of the iterative approach, which is necessary to judgements concerning model convergence. Retention of race in the hazard increased model convergence due to collinearity, and when dropped model fit was improved.

rate which was slightly lower than the 10 percent reoffending rate for federally targeted gang members. Among state charged gang members, the reoffending rate was even lower at only 1 percent.[34] The results of the tie-based infection measures were then scrutinized by a degree measure that captures the embeddedness of each gang member in the network. Embeddedness accounted for all incoming and outgoing ties a gang member had over the course of the study. The mean averages for untargeted, federal, and state targeted actors on this measure were 9.5, 38.89, and 47.6, respectively. These averages confirmed that the most embedded actors were those charged by the FBI. In the graph depicted in Figure 13, Igraph was used to visualize the embeddedness of the actors in relation to their role as bridges in the network. This graph

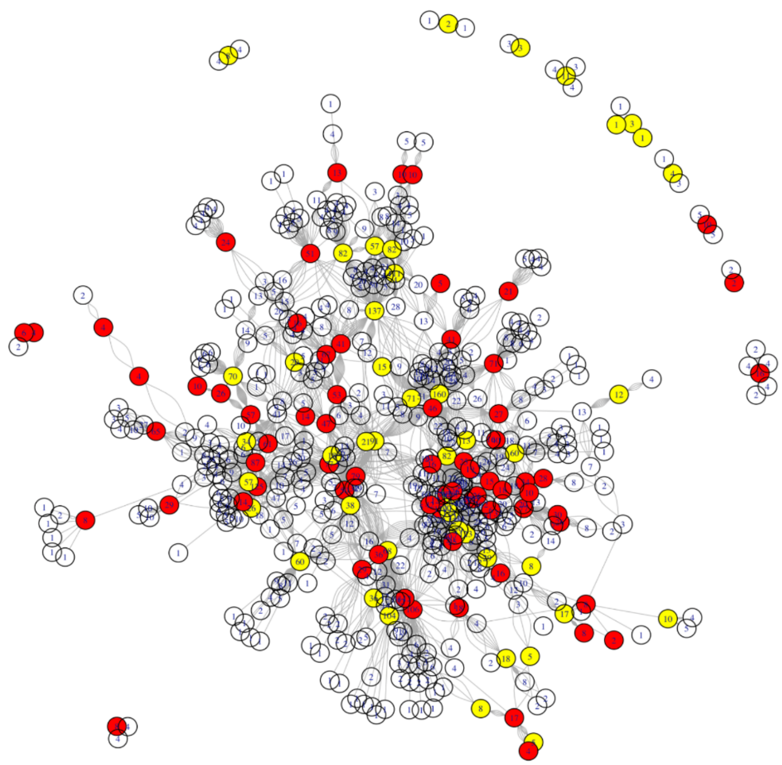

Figure 13: Actor degree for the Lynn Network (Federal=Red, State=Yellow)

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[34] With regards to the lack of a hazard risk found for federally charged gang members, population differences were considered. Given that the total number of federal targets (N=69) exceeded the number of state targets (N=45), this supports the conclusion that federal targeted gang members responded differently to punishment.

confirms that state and federally charged gang members occupied positions ideally suited to diffuse information on risk to others in the network. Yet this did not occur.

In the graph, the observed clustering of actors was considered as a possible explanation. Clustering has been previously associated with ‘small-world’ criminal networks described as “loosely networked, small clusters of individuals” (Malm and Bichler, 2011:274). These small world structures are evaluated by the density of the network, the number of network clusters present, and the clustering coefficient measure. In the Lynn network, there was very low network density, a high number of clusters (113), and a clustering coefficient (.32) that indicated more interactions within the clusters of the structure. These are all consistent with a small world network structure (Malm and Bichler, 2011). In the criminal network examined by Malm and Bichler (2011), clustering was proposed as a mechanism that might produce redundancy in a criminal organizations’ ability to carry out its activities. However, based on the low offending rates reported for the gang members in Lynn, offender replacement did not appear to have taken place.

Clustering has also been considered by network researchers for its’ influence on communication patterns within a network structure through the heuristic device known as community. This device models the effects of clustering through a probability-based algorithm that highlights communication patterns predicted to occur in a structure based on the observed ties between individuals (Rosvall and Bergstrom, 2008). In the figure below, this heuristic device was applied to the Lynn gang network in order to examine whether clustering might explain the lack of effect found for social tie influence in the contagion measures. The fields depicted in the graph that surround the actor clusters reflect the community heuristic and

predicted communication patterns based on the co-offending ties between targeted and untargeted gang members collected during the study period.

On the upper right periphery of the network, the referenced subgroups by the FBI who cut across gang affiliation lines highlight how such communities may have restricted the flow of risk information to clusters based on aspects of trust and exchange. Within the denser areas of the network clustering appears even in the larger communities, which may have played a role in restricting the flow of information and influence through the larger relational structure of the Lynn gang network.

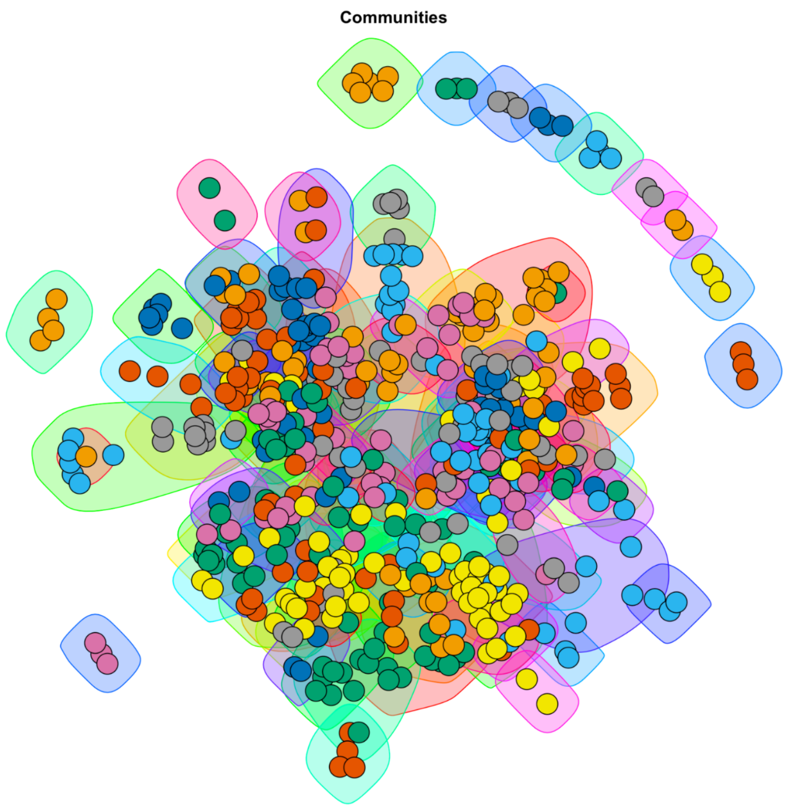

Figure 14: Communities in the Lynn Gang Structure

In figure 15 below, a network section was isolated to further demonstrate the potential linkage between the patterns in gang member connections and communication consistent with the network heuristic of community. In this section, the high levels of reciprocity reported in the diffusion model carry forward in the visualization of the constrained interactions that took place

between cooffenders in the Lynn gang network. For instance, the bulk of interactions observed for the federal target with 24 ties takes place principally among the same 5 individuals. This frequency can be extrapolated to the community figure where the predicted communication for this federal target would have taken place in this cluster of gang actors.

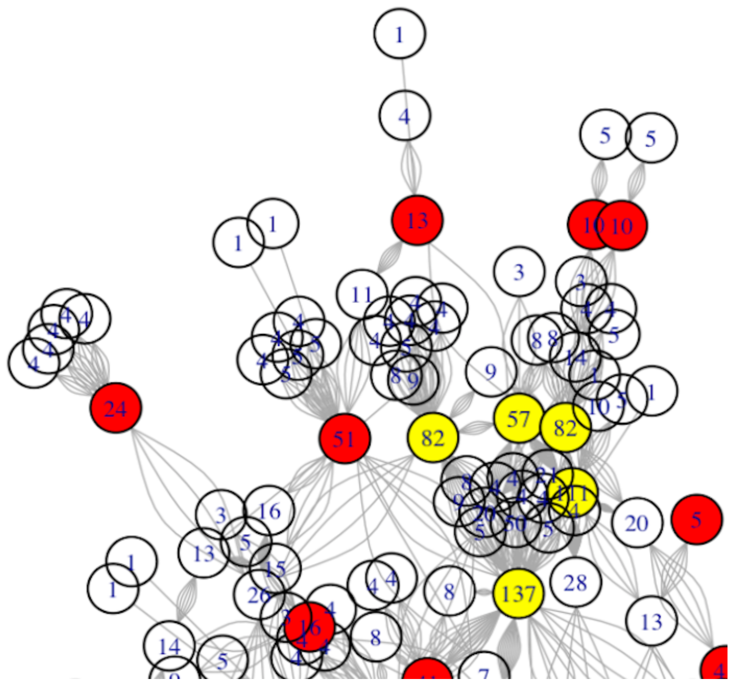

Figure 15: Social Tie Patterns Within Clusters (Illustrative Highlighted Section)

The last figure presented in this study brings attention back to the question of the overall impact that the FBI's diffusion campaign had against the street gangs in Lynn. Notwithstanding the constraints that appeared to operate because of the high degree of clustering in the network, figure 16 provides the snapshot of gang member behavior at the end of the study period. This provides a visual sense of which gang members in the network desisted from committing violence and drug offenses. In the graph, individuals who did not offend are coded 1 and 0 otherwise. Visually, the low offending rates observed among the gang members of this study appear as part of a network that saw substantial changes in the behaviors of its members. Yet simultaneously, variations in gang member response appear within the network clusters created

by the conditions of trust and exchange between the gang members in Lynn. In this respect, clustering also appeared to influence the offender response, potentially through a limited offender replacement process.

Wave 6

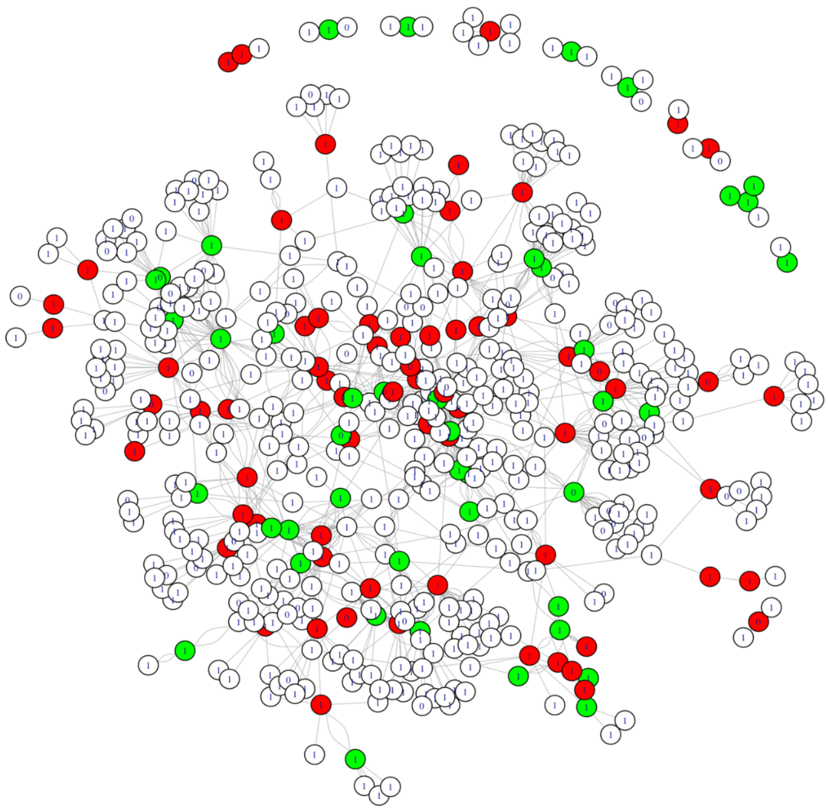

Figure 16: Gang Member Behavior at Wave 6

However, a further exploration of such questions is not possible with the models of this research given that the Stochastic Actor Oriented Model is restricted given the actor-oriented statistical approach to evaluations of network change at the individual level. However, in this first application to a cooffending network of gang offenders, the model revealed clustering to be a potential conditioning factor ripe for further examination in future studies.

CHAPTER 5

CONCLUSIONS AND LIMITATIONS

The street gang problem in the city of Lynn began innocuously enough. Following the collapse of the Khmer Rouge in 1979, refugees from Cambodia were resettled in cities across the United States including Lynn. Over the ensuing decade, the city became home to a large migrant community, but by the early 1990's, Cambodian youth in the city began to come to the attention of authorities because of their involvement in minor delinquency incidents such as truancy, and fighting in school. According to police officials, the Cambodian groups as well as others in the city, became transformed into a number of competing gang 'sets' following the entry of nationally aligned Bloods and Crips street gangs in Lynn. Gang violence that had been traditionally skirmish-based and rarely lethal took on a new form because of the desire of local gangs to be associated as a Blood, Crip, or Latin King gang member. As more rigid gang affiliation became established, violence in the city became connected to an escalating series of reciprocated incidents that culminated in the 2000 murder of the Bloods gang leader in Lynn (United States Attorney, District of Massachusetts, 2010).

From this murder, a decade of violence that raged on the city's streets was set in motion. Initially, local law enforcement officials attempted to handle the gang problem through traditional enforcement efforts as well as through partnering with community outreach groups and other agencies such as the Department of Youth Services (DYS), Department of Children and Families (DCF), and the probation departments of the juvenile and adult courts. A number of 'Shannon Grant' initiatives—state funded gang efforts— were also attempted to reduce gang violence by providing alternatives to gang involvement through educational and employment opportunities for current gang members and those at risk of joining the groups. These efforts

included many attempts to facilitate dialogue and mediate conflict between the street gangs in the city.

However, when these efforts failed to impact the ongoing gang violence in the city, Lynn police officials turned to the Department of Justice and Federal Bureau of Investigation for assistance under the Department of Justice's Safe Streets Violent Crime Initiative and the National Gang Strategy. In 2005, the FBI created the North Shore Gang Task Force to target the groups in Lynn responsible for violence as part of the agency's National Gang Strategy, and in efforts supported by the FBI's Enterprise Theory of Investigation (Decker, 2002). The FBI's application of this investigative strategy in Lynn followed a template consisting of three interrelated stages; beginning with the gathering of intelligence to determine the structure, membership and activities of violent street gangs (Decker, 2002). This in turn channeled the focus of the North Shore Gang Task Force on the key locations where the gangs operated, and the identities of the key players orchestrating violence and coordinating the activities of the Lynn street gangs (Weisel, 2002). As Weisel (2002) has noted, who communicates to whom is one of the key areas that the FBI focuses upon in relation to understanding the coordination of criminal enterprise in the groups. The third stage of Enterprise Theory of Investigation is linked to the structured prosecution approach where the consideration of appropriate sanctions is framed by the application of RICO statutes and other enterprise violations to gang leaders and other highly involved gang members (Weisel, 2002).

In Lynn, what was begun as a short-term enterprise theory of investigation eventuated into a longer-term effort that targeted the key "leaders, members and associates of the Avenue King Crips, the Bloods, the Gangsta Disciples, the Deuce Boyz, and the Latin Kings" (United States Attorney, District of Massachusetts, 2010). Over the course of five North Shore Gang

Task Force operations, 69 gang members would be charged with violations of federal enterprise offenses, while 45 other members were sanctioned in connection to serious state law violations (United States Attorney, District of Massachusetts, 2010). According to officials involved with the implementation of these efforts, the arrests of 'impact players' and their removal from the community was expected to lead to reductions in city violence given their roles in directing group-based violence and their involvement with gun and narcotic trafficking.[35]

In this study, the Stochastic Actor Oriented Model and its coevolution component was used to examine whether the efforts of the FBI and its Enterprise Theory of Investigation strategy reduced offending among targeted and untargeted gang members. This coevolution model parsed the punishment effects of incarceration and specific deterrence among targeted members and general deterrence effects through the behavioral effects of alter and ego, and similarity. Alter and ego captured the impact of desistance among gang members who more popular or active, while the similarity effect indicated whether Lynn gang members came to share ties because of the cumulative impact of sanctions on the network. With these effects controlling for one another in the study models, only gang members targeted by the FBI were found impacted by sanctions.

This study also found that Lynn gang members sanctioned for enterprise violations saw no increase in their hazard for desistance while those convicted for state law violations, and who received less prison time, saw a statistically significant increase in their risk. As a major finding of this study, the distinction which has supported the claims of FBI task forces and justified the

[35] In the Melting Pot operation alone, "authorities seized 34 guns, including two SKS rifles, two Tech-9 semi-automatic machine guns, a Mac 11 semi-automatic machine gun, two sawed off shotguns, a .40 caliber submachine gun, an AR-15 assault rifle, and a 50-caliber handgun. Over a kilogram of crack, two kilograms of cocaine, a half kilogram of heroin, approximately seven pounds of marijuana, and approximately $40,000 in cash were also purchased or seized" (United States Attorney, District of Massachusetts, 2010).

application of enterprise statutes—the severity of punishment—simply failed to statistically impact gang members who experienced lengthier sentences of incarceration. On the question of specific deterrence and consistent with prior research, this study found "little evidence of a specific deterrent effect arising from the experience of imprisonment" among the federal targets of the FBI (Nagin, 2013:210). The significant risk for state convicted gang members however, raises the issue as to why punishment threats were viewed by these offenders as credible.

In the concept of deterrability where perception is framed as the offenders' willingness to weigh risk and rewards, a potential explanation rests with distinctions in terms of the network activity between federal and state targets. As noted, state charged gang members were higher in their average network activity than the federal targeted members. In the group context, Jacobs (2010) has indicated one of the factors that may influence deterrability is the capacity to hear about what happened to others, and in this case, it may have contributed to increased perceptions of punishment *certainty*. This is what Stafford and Warr (1993) also referred to as vicarious experience with punishment, which has been proposed to operate alongside direct experience to produce variations in individual perception of risk. In the case where punishment certainty has been the most supported punishment principle in previous research, the hazard rate difference between state and federal convicted gang members supports a similar conclusion (Nagin, et al., 2015).

This study also set out to evaluate the nexus between objective risk level changes and perceptual response with gang offenders in Lynn who were not subjected to sanctions. Consistent with claims made by the North Shore Gang Task Force, officials connected the enforcement efforts in the city with a broader-based impact through the messages that had been sent by targeting gang leaders. The diffusion of innovation framework located these claims

among the social tie connections between gang members where information on changes in objective risk levels would travel within the targeted groups themselves. The diffusion of innovation model allowed for the tracing of behavioral change through the cooffending ties of Lynn gang members consistent with a networked-based conceptualization of risk under the marginal deterrence hypothesis. In the social tie measures of the study, gang members who were connected generally to others who had desisted, and directly to those targeted, saw no change in their perceptions of risk. In the second major finding of this study, the wider impacts claimed by the FBI from their concentrated enforcement efforts did not materialize in the behavioral response to messages sent along the channels of communication in the gang network.

IMPLICATIONS FOR POLICY AND RESEARCH

The Federal Bureau of Investigation's approach to street gangs is based on the view of the groups as a form of criminal enterprise whose use of violence and involvement in the trafficking of guns and drugs threatens communities. The partnering of federal, state, and local law enforcement with street gang intelligence shapes a targeted response and a structured prosecution strategy that emphasizes punishment severity in the application of federal enterprise statutes. In light of their enforcement activity, and its' status as the FBI's premier gang strategy, one would expect these efforts to be among the most researched public policies and the effectiveness of Enterprise Theory of Investigation in reducing gang violence well-established; however, this is not the case.

This is only the third criminological study to evaluate the Safe Streets Gang Strategy initiative, and "while central to FBI gang violence reduction", the effectiveness of Enterprise Theory of Investigation has been based exclusively on the claims of officials carrying out the efforts (Ratcliffe, Perenzin, and Sorg, 2017:454). This lack of research has framed concerns over the involvement of the FBI in localized crime problems where the burden of federal statutory

enforcement has been borne by poor and minority communities (Phillips, 2012). For instance, Woods (2011) found that Black, Latino or Asian gangs constituted nearly 86% of RICO prosecutions filed between 2001 to 2011, while 83% of individuals prosecuted under the law were ethnic or racial minorities. A major criticism flowing from these Task Force's enforcement of enterprise crime is that they rely on a "rhetorical nexus between gangs, drugs, and violence…[to advance] law enforcement core functions" [as well as] "drug prosecution as the best way to target…violent offenders" (Phillips, 2015: 121,124). Parenthetically, sourced from unsupported law enforcement claims of effectiveness, critics have charged that the growth of these initiatives has combined with enterprise enforcement to create a pathway for minority entry into the federal prison system for mostly non-violent drug offenses (Phillips, 2015).

As an example of growth, the FBI's North Shore Gang Task Force has expanded its enforcement efforts throughout Massachusetts and into all of the New England States as part of the ongoing Safe Streets Gang Strategy. In 2016, the task force was credited with the most extensive investigation involving the MS-13 street gang. Following a five-year, multi-state investigation involving Massachusetts, Rhode Island, Connecticut and New Jersey, the group was credited in 2019 with the largest 'takedown' of the Latin King Street Gang (Wagner, 2019). In the context of the two previous studies conducted on the strategy, the results of the current research lend validity to critic concerns.[36]

While FBI officials had indicated they had sent a strong message to gang members in Lynn and elsewhere, this was found not to be the case. The only statistically significant impact

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[36] The results of the two pre-existing studies were mixed. In the first study of a Safe Street Task Force initiative, Nunn and colleagues (2006) examined the targeting of a loosely structured group of gang involved drug dealers in the Brightwood section of Indianapolis in 1999. Service calls for drugs in the city actually increased in the 12-month period following the removal of those dealers (Nunn, et al., 2006). In the other study, a 22% decline in violent crime incidents was seen in the nine-month period following the indictment and sentencing of 23 gang leaders in South Central, Los Angeles before rates returned to their previous levels (Ratcliffe, Perenzin, Sorg, 2017).

was seen with those who were convicted of state charges; in direct contradiction of the justifications for the use of more severe punishments, and the structured prosecution approach of the Safe Streets Gang Strategy. Similarly, race was found in this research to be a major influence in the social ties of Lynn gang offenders despite indications by law enforcement that the street gangs were more diverse than those found in other cities in the country. Given the limited support found in this study for the strategy, much more research will be needed to confirm the results of this, and to address concerns raised by the failure of enterprise enforcement to impact perceptions of risk for those targeted.

In this regard, the strategy would benefit from the type of researcher partnerships that have established the pulling levers focused deterrence strategy as the most well researched anti-gang strategy (Braga, 2008; Braga, Weisburd and Turchan, 2018). In the current state of Safe Streets Gang Strategy research, a particular irony arises in the fact that pulling levers focused deterrence and the Safe Streets Violent Gang Initiative are both supported by the Department of Justice's $1.5 billion dollar Project Safe Neighborhoods program (Peterson and Bushway, 2020). Despite debate concerning the marginal deterrence hypothesis and the nexus of perception, and the consensus that severity-based approaches to crime are ineffective, the Safe Streets strategy has remained on the sidelines of researcher interest (Peterson and Bushway, 2020; Nagin, Solow and Lum, 2015; Clear and Frost, 2014; Durlauf and Nagin, 2011). In her own research, Phillips (2015) has described a situation where FBI officials are not willing to be engaged with the research community; evidenced by the circumstances of the study conducted by Ratcliffe et al.,

(2017). In that case, researchers were involved with another project when they learned of the FBI effort in Los Angeles that formed the basis of their study.

Beyond implications for the Safe Streets Gang Strategy, the results of this research resonate more broadly with recent trends focusing on perception in deterrence theory and the importance of communication in gang-based efforts. As a network-based theory predicated on communication processes between socially connected individuals, questions of perception and response to sanctions and threats became grounded to social tie interactions within a network structure of a street gang. The specific deterrence distinctions found among state and federal targeted gang members indicate an area for further exploration in the tradition of Bayesian-based research concerned with the risk updating process. In the current study, an explanation for the differences found in this study was offered consistent with the proposals of Jacobs (2010) and Stafford and Warr (1993). A researcher interested in the updating process could incorporate offender surveys with these models to more fully develop the factors affecting individual perception and response in these types of deterrence campaigns. For example, information on impulsivity could be incorporated in accounting for individual differences in hazards with and without contagion measures, and its impact on the coevolving structure of network ties could also be evaluated.

The failure to find support for social tie mechanisms linking objective risk to changes in perception also draws attention to dominant assumptions in street gang policy relating to communication and the impact of punishment threats. Many of these group-based proposals were reflected directly or indirectly in this study. For instance, focused deterrence strategies have advanced a deterrence-based mechanism that links to street gangs conceived as the "internal communication vehicle" for information on punishment risk to be transmitted to other

offenders, especially in cases where individuals are sanctioned for noncompliance in the group context (Braga, Weisburd, and Turchan, 2018:7). Building upon this principle, the models in the study reconceptualized the FBI's effort in Lynn as a deterrence-based network intervention. In the diffusion framework and analytic models, the communication vehicle and unit of analysis for perception centered on the social ties between gang members. Consistent with these serving as the communication flow network structure for information on risk to pass in the groups, the perceptual impact was traced from the targeted leaders to others in the decision to desist from crime.

In the null effects found for social tie influence in the SAOM, a number of potential avenues exist for future research to expand on the relationship between gang structure and communication . For example, McGloin (1995) had used the bridge position as the basis for the 'cut-point'; gang members who span clusters of structure. The cut-point was offered for its potential to enhance the effectiveness of anti-gang efforts by focusing on these network positions (McGloin, 1995). The notion of the cutpoint was confirmed in this research as the gang leaders targeted by the FBI occupied these positions; however, this study was not designed to scrutinize this role, and future models could be implemented to reflect the removal of these actors. Piquero et al. (2011:347) had also indicated that the cutpoint could affect "both the ability to [be] deterred and the ability to deter another…because [of the fact that] deterrence involves a process of threat communication". In this regard, the potential for producing a more salient deterrence message in gang or criminal offender networks was connected to the transmission of information to a broader set of actors across clusters (Piquero, et al., 2011).

In this first application of the Stochastic Actor Oriented Model involving a network of cooffenders, the cutpoint/bridge function failed to materialize in the social tie assessment of

communication and risk. In this research, these individuals were expected to function as opinion leaders whose punishment would communicate risk to others in the network broadly as well as more directly through the gang leaders' social tie connections. On both accounts, the punishment of gang leaders failed to in influence the behavior of others. The study then turned to norms of trust and exchange, which were reflected in the tendency of Lynn gang members to reciprocate and maintain their social ties. This gave rise to a communication flow relational structure constrained in its ability to communicate risk and to activate peer influence processes beyond clusters. While the dyadic network relationship has featured prominently in previous studies and discussions, its relationship to communication of risk had not been precisely identified.

For example, the cutpoint principle developed from the tendency towards reciprocity in the dyad. In her study of gangs in Trenton, New Jersey, the majority of gang offenders reported cooffending with the same individual, and in the random patterns of ties of all offenders, certain actors came to occupy these bridge positions. McGloin (1995) visualized these more in the disruption frame as opposed to a deterrence and communication frame. In a later network redundancy framework, the dyadic tendency was used to access the impact of reciprocated ties on the offending versatility of serious juvenile offenders consistent with opportunity theory (McGloin and Piquero, 2010). Described as "the overlap among contacts in one's social network", dyadic relationships were found to limit the types of offenses committed by individuals within the group setting precisely because the structure limited information and the opportunity to participate in a wider category of offenses (McGloin and Piquero, 2010:65). In a more recent study examining cooffending patterns in Chicago, Charette and Papachristos, (2017) found remarkable durability in the reciprocated relationships of offenders over the course of an

eight-year period. It should be noted that the ties accessed among Lynn offenders spanned a greater period and indicated even stronger preferences for reciprocity than those reported in Chicago.

In the current study, effects of 3-cycle and reciprocity were used in models to connect the norms of trust and exchange with their relationship on the larger relational network structure. More specifically, these reflected a small world network consisting of a loosely structured set of clustered individuals. Relationships formed when many of the subjects were juveniles, and which continued into early adulthood, were reflected in trust and exchange interactions that conditioned network communication. The heuristic device of Community provided some insights into how communication may have been constrained based on these longstanding tie preferences during the time of the FBI operations. In the network-based concept of social contagion, "actors are susceptible to becoming "infected" with certain beliefs, behaviors, and attitudes by virtue of their relations in a network" (Contractor and Forbush, 2017:17). For Lynn gang members, this susceptibility appeared limited to the clusters of the network, and sufficient to undermine the bridge position and the role of the targeted gang members in promoting behavior change through interpersonal communication under the diffusion of innovation framework (Valente, 1999).

Of course, there is the possibility that none of the structural elements conditioned a response if gang members chose to purposely ignore the communicated threat messages sent by the FBI. As Zimring and Hawkins (1973:157) have noted, "to conceive threat as communication makes explicit the fact that the perceptions of an audience, rather than the threat as intended by the agency, will determine the degree to which legal threats will achieve desired goals". In this regard, the subjective judgements of Lynn gang members towards apprehension and punishment

could have simply remained unchanged despite the enforcement and severe sanctions that were directed at the groups in Lynn. In this possibility, much more research is needed in order to evaluate the question of structure, communication and perceptual response in light of wide variations that are to be expected across gang contexts and populations. It is also possible that the restraining effects on cooffending opportunity identified by McGloin and Piquero (2010) is a universal aspect of trust and exchange, which extends into gangs to restrain communication, and contradict proposals of organized street gangs. Future research as well is needed, which could incorporate offender surveys to identify social tie relationships from which other channels of communication on risk may be sourced. Of course, these surveys could also be used to gather additional information on relevant characteristics on offenders themselves as noted above, and to gather a more precise understanding of the offender's perception of risk.

In this regard, the expansion in use of these models with active offenders, and their assumptions of dependency would address a need identified by Culler (2010:310; 312) for criminologists to "study the concrete conditions [of crime, and] the assumption…that contexts affect individuals mainly because they are composed of people who possess shared beliefs (culture) and engage in shared action". In this regard, Greenan (2015) has noted the diffusion of innovation model has potential for analytic flexibility in the expansion of the state space of the behavioral dependent variable. This expansion would allow the hazard model to become a Poisson process that would allow for measuring adoption as a "number of events" in order to model how many times the behavior is performed (Greenan, 2015:163). In this way, a researcher could use the model to evaluate hazard patterns that extend into changes in behavior, such as the

onset and desistance from crime dependent on a coevolving network of offending ties in a study population.

The application of these models is fraught with challenges, however. The data required to implement them is not readily available or easy to access by researchers. This author was fortunate to have a relationship with the Lynn Police Department that allowed access to the data sources necessary to construct and analyze the relational networks of the study. The data structure required for social network analysis is much different than what is used by criminologists, and this in of itself is a challenge when constructing study data. Adding to uncertainty, once assembled, there are no guarantees that the data will work for the purpose in which it was constructed (Faust and Tita, 2019; Ripley, et al., 2018). The researcher will also need a good working knowledge of the R computing environment and the programming language required for implementing models in the Igraph and R Siena packages.

STUDY LIMITATIONS

The findings of this research are tempered by a number of limitations. Beginning with the study data, researcher decisions may have influenced the model results. For instance, the sampling procedures used in the study relied on official police records, which typically raise concern with official bias, but in the network context, raise concerns about network boundaries in cases where ties are not fully captured (Malm and Bichler, 2011). Additionally, meanings attached to social tie connections have varied widely in the criminological studies that have used network methods, and accordingly, caution has been advised in the interpretations drawn in any one particular research study (Faust and Tita, 2019; Sierra-Arévalo and Papachristos, 2015). With the 'multi-system' sampling procedures intended to bolster confidence in the identification of the network boundaries of Lynn street gangs, a positive indication was the later identification of targeted gang members in criminal history records after sampling had been conducted.

Nonetheless, there is no certainty that all of the relations that existed between offenders were obtained through the use of these procedures.

Additionally, the researcher decision to structure data in waves from targeted to untargeted gang members during the enforcement efforts is another potential limitation. More specifically, this decision was intended to model the cumulative effects of sanctions from the early innovators and opinion leaders of desistance behavior—the targets of the FBI. The structure of 'upward ties' may have mischaracterized the full spectrum of interactions that may have taken place between the members of the Lynn gangs, while potentially biasing the behavioral effect for ego (e.g., relational data derived from the ego-centered networks of targeted actors). Furthermore, this data structure resulted in time variations in the hazard model for gang members based on when they entered. In this way, survival times may have conditioned the reported results, but the model cannot account for these differences in exposure time.

This study also is limited by the social network-based approach in satisfying established standards as it relates to issues of internal and external validity, causation, and sampling methods. In evaluative research, the gold standard for establishing internal validity is the randomized experimental study (Weisburd, et al., 2001). The random assignment of a study population among a control and treatment group allows the researcher to account for unobserved influence in experimental studies, while enhancing confidence that a treatment was the cause of the outcome (Weisburd, et al., 2001;Weisburd, et al., 1993). In the field of the social sciences, the gold standard has been difficult to realize because of ethical concerns, but through the quasi-experimental design, criminologists have sought to establish greater confidence in the particular results of policy interventions (Weisburd, 2010; Welsh, et., al. 2010). This design addresses issues of internal validity and causality by allowing "investigator control over allocation to

treatment" (Sampson, 2010:490). As part of a 'best practices' approach to evaluative research, these types of designs are best encapsulated by standards set forth under the Maryland Scientific Method Scale of Sherman and colleagues (1997), and with the history of experimental research design in pulling levers focused deterrence research (Braga, et al., 2018; Braga, et al., 2014).[37]

The Stochastic Actor Oriented Models in this study cannot address internal validity through the Maryland scale or in reference to evaluation standards developed by researchers in more recent focused deterrence research (Braga, et al., 2018; Weisburd and Majmundar, 2018). However, as grounded research, the observational nature of this study is more concerned with the types of selection and influence biases that dominate the discourse in network-based studies of behavior (Shalizi and Thomas, 2011; Steglich, et al., 2010). Therefore, the greatest threat to internal validity in this study concerns unaccounted influences that may have contributed to changes in gang members behavior. As noted, the network of ties in this study followed the timeline of police response in Lynn from local enforcement efforts to those of the FBI's North Shore Gang Task Force. While this researcher has not obtained information to indicate that any other law enforcement or substantial community-based effort was active during this study period, if this was the case, it would bias the study results. Similarly, this study placed the direction of causality for gang desistance squarely with the social tie, but this of course may not have been the only influence in decisions to desist. For instance, the study cannot account for cases where a gang member was driven to desist because they themselves or those associated with them were victims of violence. In this regard, there could have been many instances of violence incidents that went unreported to police and therefore were not able to be identified. It is also possible that

[37] These claims are not without critics. Sampson (2010) raised issue with the way in which benefits of randomization were represented. More specifically, random assignment did not settle the issue of non-random sample bias arising from the types of populations studied in criminological experiments, nor did it provide the level of causal inference arising from data that would speak for itself (Sampson, 2010:491).

some offenders may have changed their behavior because they got old, got a job, or had some other life altering event (Charette and Papachristos, 2017).

In terms of external validity, this is the first case study of a gang network using the Stochastic Actor Oriented Model. Therefore, the ability to generalize study findings is limited and external validity as it currently exists, would be confined to the city of Lynn and its street gangs. However, if further studies produce similar findings in other cities and among other gangs, this would help establish the validity of the study's conclusions. The last area of limitation concerns model power, which has just begun to be explored in stochastic models (Stadtfeld, et al., 2018) "In classic power studies…power depends on three parameters: the significance level, sample size, and effect size…[that determine] the probability to (correctly) reject the null hypothesis when the alternative hypothesis is true [type II error]" (Stadtfeld, et al., 2018:3). Because of the dependency assumptions in network models, significance cannot be tested in the same way in which it is tested in regression models. However, two of the criteria that have been included in preliminary discussions of power are sample size and the loss of network ties (Stadtfeld, et al., 2018). In both criteria, this study would meet thresholds for sufficient sample size and tie loss as no ties were removed from the network. Future development in this area will be helpful for external validity in studies using these models.

In this study of deterrence and gangs, the implementation of a diffusion of innovation model reflected calls for special approaches to the study of deterrence and for network-based analyses of street gangs and gang dynamics (Sierra-Arévalo and Papachristos, 2015; Apel, 2013; Tonry, 2008). This research fused the conceptualization of deterrence as a punishment threat system with a network-based intervention framework that grounded the communication mechanism of the deterrence-based street gang strategy in the targeted groups. Under the

Diffusion of Innovation analysis, the social tie became the central measure for both communication of risk and the assessment for perception of risk. While the results of this study indicated little social tie influence on the behavior of Lynn gang members, the analysis revealed a previously unidentified interaction between network structure, communication and peer influence processes as it relates to punishment risk.

In this regard, whether patterns of gang homicide or the communication of deterrence is studied, the social network approach has much more potential to illuminate the black boxes that operate in these groups. Going forward, it is hoped that researchers would embrace this type of network modeling especially as an adjunct to the dominant quasi-experimental methods in existing gang studies. In the larger frame of public policy concern, deterrence is as old as it is controversial and with the addition of network-based approaches, a new avenue for developing understanding in the relationship between sanctions, threats, and perception of risk may be at hand with the diffusion model.

REFERENCES

Agnifilo, M., Bliss, K., & Riordan, B. (2006). Investigating and Prosecuting Gangs Using the Enterprise Theory. In J. Donovan (Ed.), *Gangs*. Department of Justice Executive Office for United States Attorneys.

Allison, P. D. (1999). *Multiple regression : a primer*. Pine Forge Press.

Anderson, E. (1999). *Code of the Street*. Norton.

Anwar, S., & Loughran, T. A. (2011). Testing a Bayesian Learning Theory of Deterrence Among Serious Juvenile Offenders. *Criminology*, *49*(3).

Apel, R. (2013). Sanctions, Perceptions, and Crime: Implications for Criminal Deterrence. *Journal of Quantitative Criminology*, *29*, 67-101.

Ball, R., & Curry, G. D. (1995). The Logic of Definition in Criminology" Purposes and Methods for Defining "Gangs". *Criminology*, *33*(2).

Becarria, C. (1764). *On Crimes and Punishment*. The Federalist Papers.

Becker, G. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, *78*, 526-536.

Bell, J. C. (1955). Deterrence Concept in Criminology and the Law. *Journal of Criminal Law and Criminology*, *46*(3).

Bentham, J. (1988). *The Principles of Morals and Legislation*. Prometheus Books.

Berg, M. T., Stewart, E. A., Schreck, C. J., & Simons, R. L. (2012). The Victim-Offender Overlap in Context: Examining the Role of Neighborhood Street Culture. *Criminology*, *50*(2), 359-390.

Block, C. R., & Block, R. (1993). *Street Gang Crime in Chicago*. Washington, D.C.: National Institute of Justice

Blumstein, A. (2001). Why is Crime Falling-Or Is It? Perspectives on Crime and Justice: 2000-2001 Lecture Series, Washington, D.C.

Blumstein, A., Cohen, J., & Nagin, D. (1977). *Deterrence and Incapacitation-Estimating the Effect of Criminal Sanctions on Crime Rates*. Washington, D.C.: National Academy of Sciences

Borracci, R. A., & Giorgi, M. A. (2018). Agent-based computational models to explore diffusion of medical innovations among cardiologists. *International Journal of Medical Informatics*, *112*, 158-165.

Bowers, K., Johnson, S., Guerette, R., Summers, T., & Poynton, S. (2011). Spatial Displacement and Diffusion of Benefits among Geographically Focused Policing Initiatives. *Journal of Experimental Criminology*, *7*(4), 347-374.

Braga, A. A. (2001). The Effects of Hot Spots Policing on Crime. *The ANNALS of the American Academy of Political and Social Science*, *578*(1), 104-125.

Braga, A. A. (2007). The effects of hot spots policing on crime. In (9 May, 2007 ed., pp. 36): The Campbell Collaboration.

Braga, A. A. (2008). *Problem-oriented policing and crime prevention* (2nd ed.). Willow Tree Press.

Braga, A. A. (2008). Pulling levers focused deterrence strategies and the prevention of gun homicide. *Journal of Criminal Justice*, *36*, 332-343.

Braga, A. A., Apel, R., & Welsh, B. C. (2014). The Spillover Effects of Focused Deterrence on Gang Violence. *Evaluation Review*, 1-29.

Braga, A. A., & Bond, B. J. (2008). Policing Crime and Disorder Hot Spots: A Randomized Control Trial. *Criminology*, *46*(3), 577-608.

Braga, A. A., & Douglas, S. (2021). The Influence of Bentham on the Development of Focused Deterrence. In S. Jacques & P. Schofield (Eds.), *Jeremy Bentham on Police: The unknown story and what it means for criminology.* UCL Press.

Braga, A. A., Hureau, D. M., & Papachristos, A. V. (2013). Deterring Gang-Involved Gun Violence: Measuring the Impact of Boston's Operation Ceasefire on Street Gang Behavior. *Journal of Quantitative Criminology*, *30*, 113-139.

Braga, A. A., Kennedy, D. M., Piehl, A. M., & Waring, E. J. (2000). *The Boston Gun Project: Impact Evaluation Findings*. Washington, D.C.: National Institute of Justice

Braga, A. A., Weisburd, D., & Turchan, B. (2018). An Updated Systematic Review and Meta-Analysis of the Empirical Evidence. *Criminology and Public Policy*, *17*(1).

Braga, A. A., & Weisburd, D. L. (2012). The Effects of Focused Deterrence Strategies on Crime: A Systematic Review and Meta-Analysis of the Empirical Evidence. *Journal of Research in Crime and Delinquency*, *49*(3), 323-358.

Brantingham, P. J., & Brantingham, P. L. (1999). A Theoretical Model of Crime Hot Spot Generation. *Studies on Crime and Crime Prevention*, *8*(1), 7-26.

Charette, Y., & Papachristos, A. V. (2017). The network dynamics of co-offending careers. *Social Networks*, *51*(3), 13.

Clarke, R., & Cornish, D. (2001). Rational Choice. In R. Paternoster & R. Bachman (Eds.), *Rational Choice*. Oxford University Press.

Clarke, R. V., & Cornish, D. B. (1985). Modeling Offenders' Decisions: A Framework for Research and Policy. In M. Tonry & N. Morris (Eds.), *Crime and Justice: An Annual Review of Research* (pp. 147-185). University of Chicago Press.

Clarke, R. V., & Weisburd, D. (1994). Diffusion of Crime Control Benefits: Observations on the Reverse of Displacement. *Crime Prevention Studies*, *2*, 165-183.

Clear, T. R., & Frost, N. A. (2014). *The Punishment Imperative: The Rise and Failure of Mass Incarceration in America*. New York University Press.

Cohen, L. E., & Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*, *44*(4), 588-608.

Contractor, N., & Forbush, E. (2017). Networks. In C. R. Scott & L. Lewis (Eds.), *The International Encyclopedia of Organizational Communication*. John Wiley and Sons.

Cook, P., T, & Laub, J., H. (1998). The Unprecedented Epidemic in Youth Violence. *Crime and Justice*, *24*, 27-64.

Cook, P. J. (1980). Research in Criminal Deterrence: Laying the Groundwork for the Second Decade. *Crime and Justice*, *2*, 211-268.

Cullen, F. T., & Agnew, R. (2013). *Criminological theory : past to present : essential readings* (5th ed.). Oxford University Press.

Curry, G. D., & Spergel, I. A. (1988). Gang Homicide, Delinquency, and Community. *Criminology*, *26*(3), 381-425.

Decker, S. H. (1996). Collective and Normative Features of Gang Violence. *Justice Quarterly*, *13*(2).

Decker, S. H. (2002). A Decade of Gang Research: Findings of the National Institute of Justice Gang Portfolio. In W. L. Reed & S. H. Decker (Eds.), *Responding to Gangs: Evaluation and Research*. National Institute of Justice.

Decker, S. H., Katz, C. M., & Webb, V. J. (2008). Understanding the Black Box of Gang Organization: Implications for Involvement in Violent Crime, Drug Sales, and Violent Victimization. *Crime and Delinquency*, *54*(1), 153-172.

Durlauf, S. N., & Nagin, D. S. (2011). Imprisonment and crime: Can both be reduced? *Criminology and Public Policy*, *10*(1).
Eck, J. (1993). The Threat of Crime Displacement. *Problem Solving Quarterly*, *6*(3), 7.
Einstadter, W. J., & Henry, S. (2006). *Criminological theory: an analysis of its underlying assumptions*. Harcourt Brace College Publishers.
Esbenson, F.-A., Winfree, L. T., He, N., & Taylor, T. J. (2001). Youth Gangs and Definitional Issues: When is a Gang a Gang, and Why Does it Matter? *Crime and Delinquency*, *47*(1), 105-130.
Fagan, J. (1989). The Social Disorganization of Drug Use and Drug Dealing among Urban Gangs. *Criminology*, *27*(4).
Fagan, J., & Wilkinson, D. L. (1998a). Guns, Youth Violence and Social Identify in Inner Cities. *Crime and Justice*, *24*(Youth Violence), 105-188.
Fagan, J., & Wilkinson, D. L. (1998b). Guns, Youth Violence and Social Identity in Inner Cities. *Crime and Justice*, *24*, 105-188.
Faust, K., & Tita, G. E. (2019). Social Networks and Crime: Pitfalls and Promises for Advancing the Field. *The Annual Review of Criminology*, *2*, 99-122.
Fleisher, M. S. (2002). Doing Field Research on Diverse Gangs: Interpreting Youth Gangs as Social Networks. In C. R. Huff (Ed.), *Gangs in America* (pp. 199-217). Sage.
Gaines, L. K., & Kappeler, V. E. (2015). *Policing in America* (8th, Ed.). Routledge Taylor and Francis Group.
Geerken, M. R., & Gove, W. R. (1975). Deterrence: Some Theoretical Considerations. (9), 497-513.
Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual review of psychology*, *62*, 451-482.
Golbeck, J., Klavans, J. L., & Rogers, M. (2015). *Introduction to social media investigation : a hands-on approach*. Syngress.
Goldstein, H. (1990). *Problem-Oriented Policing*. McGraw-Hill.
Graevanitz, G. v., Graham, S. J. H., & Myers, A. F. (2019). Distance (still) hampers diffusion of innovations. *Regional Studies*, 1-14.
Granovetter, M. S. (1973). The Strength of Weak Ties. *The American Journal of Sociology*, *78*(6), 1360-1380.
Greenan, C. (2015). Diffusion of Innovations in Dynamic Networks. *Journal of the Royal Statistical Society*, *A*, 147-166.
Hage, P., & Harary, F. (1983). *Structural Models in Anthropology*. Cambridge University Press.
Haynie, D. L. (2002). Friendship Networks and Delinquency: The Relative Nature of Peer Delinquency. *Journal of Quantitative Criminology*, *18*, 99-134.
Hoffman, V. (Ed.). (2011). *Knowledge and Innovation Manager*.
Horowitz, M. C. (2010). Nonstate Actors and the Diffusion of Innovations: The Case of Suicide Terrorism. *International Organization*, *64*, 33-64.
Howell, J. C. (2010). *Youth Gang Programs and Strategies*. Washington, D.C.: U.S. Department of Justice
Investigation, F. B. O. (2011). *Ten Years After: The FBI since 9/11*. Bureau of Justice Statistics Federal Bureau of Investigation https://ucr.fbi.gov/ten-years-after-the-fbi-since-9-11/just-the-facts-1/violent-gang-initiatives-1
Jacobs, B. A. (2010). Deterrence and Deterrability. *Criminology*, *48*(2).
Kahan, D. M. (1997). Social Influence, Social Meaning, and Deterrence. *Virginia Law Review*, *83*.
Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus, and Girouz.
Kahneman, D. (2013). *Thinking, fast and slow* (Anchor Canada edition. ed.). Anchor Canada.

Katz, J., & Jackson-Jacobs, C. (2004). The Criminologists' Gang. In C. Sumner (Ed.), *The Blackwell Companion to Criminology*. Blackwell Publishing.

Kennedy, D. M., Braga, A. A., & National Institute of, J. (2001). *Reducing gun violence*. National Institute of Justice.

Kennedy, D. M., Piehl, A. M., & Braga, A. A. (1996). Youth Violence in Boston: Gun Markets, Serious Youth Offenders, and a Use-Reduction Strategy. *Law and Contemporary Problems*, *59*, 147-196.

Klein, M. (1971). *Street Gang and Street Workers*. Prentice-Hall.

Klein, M. W. (1993). Attempting Gang Control by Suppression: The Misuse of Deterrence Principles. *Studies on Crime and Crime Prevention*, *2*.

Klein, M. W. (1995). *The American Street Gang: Its Nature, Prevalence and Control*. Oxford University Press.

Klein, M. W., & Maxson, C. L. (1996a). *Gang Structures, Crime Patterns, and Police Responses*. Washington, D.C.: National Institute of Justice

Klein, M. W., & Maxson, C. L. (1996b). *Gang Structures, Crime Patterns, and Police Responses*. Washington, D.C.

Klein, M. W., Maxson, C. L., & Cunningham, L. C. (1991). Crack, Street Gangs and Violence. *Criminology*, *29*(4), 623-650.

Knoke, D., & Yang, S. (2008). *Social Network Analysis* (2nd ed.). Sage Publications.

Kreager, D. A., & Matsueda, R. L. (2014). Bayesian Updating and Crime. In D. Weisburd (Ed.), *Encyclopedia of Criminology and Criminal Justice*. Springer.

Kubrin, C. E., Stucky, T. D., & Krohn, M. D. (2009). *Researching Theories of Crime and Deviance*. Oxford University Press.

Lee, H. K., & Choo, H. J. (2019). Birds of a Feather Flocked Together Look Abundant: The Visual Gestalt Effect of an Assortment Presentation. *Journal of Business Research*, *104*, 170-182.

Lewin, K. (1951). *Field Theory in Social Science: Selected Theoretical Papers*. Harpers.

Lewis, K., & Papachristos, A. V. (2020). Rules of the Game: Exponential Random Graph Models of a Gang Homicide Network. *Social Forces*, *98*(4), 1829-1858.

Loughran, T., Paternoster, R., Piquero, A. R., & Pogarsky, G. (2011). On Ambiguity in Perceptions of Risk: Implications for Criminal Decision Making and Deterrence. *Criminology*, *49*(4).

Luke, D., & SpringerLink. (2015). *A User's Guide to Network Analysis in R* (1st 2015. ed.). Springer International Publishing : Imprint: Springer.

Lusher, D., Koshinen, J. A., & Robins, G. (2012). *Exponential Random Graph Models for Social Networks: Theory, Methods and Application*. Cambridge University Press.

Malm, A., & Bichler, G. (2011). Networks of Collaborating Criminals: Assessing the Structural Vulnerability of Drug Markets. *Journal of Research in Crime and Delinquency*, *48*.

McFeely, R. A. (2001). Enterprise Theory of Investigation. *FBI Law Enforcement Bulletin*, *70*(5).

McGarrell, E. F., Corsaro, N., Melde, C., Hipple, N., Cobbina, J., Bynum, T., & Perez, H. (2012). *An Assessment of the Comprehensive Anti-Gang Initiative: Final Project Report*. Washington, D.C.

McGloin, J. M. (2005). Policy and Intervention Considerations of a Network Analysis of Street Gangs. *Criminology and Public Policy*, *4*(3), 607-635.

McGloin, J. M., & Kirk, D. (2010). An Overview of Social Network Analysis. *Journal of Criminal Justice Education*, *21*(2), 169-181.

McGloin, J. M., & Piquero, A. R. (2010). On the Relationship Between Co-Offending Network Redundancy and Offending Versatility. *Journal of Research in Crime and Delinquency*, *47*(1), 63-90.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, *27*(1), 415-444. https://doi.org/10.1146/annurev.soc.27.1.415
Moldovan, S., Muller, E., Richter, Y., & Yom-Tove, E. (2017). Opinion Leadership in Small Groups. *International Journal of Research in Marketing*, *34*, 536-552.
Mongin, P. (1997). Expected Utility Theory. In J. Davis, W. Hands, & U. Maki (Eds.), *Handbook of Economic Methodology* (pp. 342-350).
Moreno, J. L. (1960). *The Sociometry Reader*. The Free Press.
Morselli, C. (2009). *Inside Criminal Networks*. Springer-Verlag.
Morselli, C. (2010). Assessing Vulnerable and Strategic Positions in a Criminal Network. *Journal of Contemporary Criminal Justice*, *26*.
Morselli, C., & Royer, M.-N. (2008). Criminal Mobility and Criminal Achievement. *45*(1), 4-21.
Nagin, D., S., Solow, R. M., & Lum, C. (2015). Deterrence, Criminal Opportunities and Police. *Criminology*, *53*(1), 74-100.
Nagin, D. S. (1998). Criminal Deterrence Research at the Outset of the Twenty-First Century. *Crime and Justice*, *23*, 1-42.
Nagin, D. S. (2013). Deterrence in the Twenty-First Century. *Crime and Justice*, *42*(1), 199-263.
O'Brien, D. (2007). DA: 5 Lynn Men Facing State Charges for Drug Bust: Behind Local Shootings and Murder also Alleged. *The Daily Item*.
Papachristos, A. V. (2009). Murder by Structure: Dominance Relations and the Social Structure of Gang Homicide. *American Journal of Sociology*, *115*(1), 74-128.
Papachristos, A. V. (2011). The Coming of a Networked Criminology. *Advances in Criminological Theory*, *17*, 101-140.
Papachristos, A. V., Hureau, D. M., & Braga, A. A. (2013). The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence. *American Sociological Review*, *3*, 417-447.
Papachristos, A. V., & Kirk, D. S. (2015). Changing the Street Dynamic: Evaluating Chicago's Group Violence Reduction Strategy. *American Society of Criminology*, *14*(3).
Paternoster, R. (2010). How Much Do We Really Know about Criminal Deterrence? *Journal of Criminal Law and Criminology*, *3*(6).
Paternoster, R., Saltzman, L. E., Chiricos, T. G., & Valdo, G. P. (1982). Perceived Risk and Deterrence: Methodological Artifacts in Perceptual Deterrence Research. *73*, 1238-1258.
Peterson, S., & Bushway, S. (2021). *Law Enforcement Approaches for Reducing Gun Violence* (Contemporary Issues in Gun Policy: Essays from the RAND Gun Policy in America Project, Issue. R. Corporation.
Phillips, S. A. (2015). The Gang-Drug Nexus: Violence, Rhetoric, and Suppression in an FBI Safe Streets Task Force. In M. W. Brienen & J. D. Rosen (Eds.), *New Approaches to Drug Policies*. Palgrave MacMillan.
Piquero, A. R., Paternoster, R., Pogarsky, G., & Loughran, T. (2011). Elaborating the Individual Difference Component in Deterrence Theory. *The Annual Review of Law and Social Science*, *7*, 336-360.
Pogarsky, G., & Piquero, A. R. (2003). Can Punishment Encourage Offending? Investigating the "Resetting" Effect. *Journal of Research in Crime and Delinquency*, *40*(1), 95-120.
Pogarsky, G., Roche, S. P., & Pickett, J. T. (2017). Heuristics and Biases, Rational Choice, and Sanction Perceptions. *Criminology*, *55*(1), 85-111.
Poole, M. S. (2013). On the Study of Process in Communication Research. *Annals of the International Communication Association*, *36*(1), 371-409.

Pyrooz, D. C., Decker, S. H., & Curry, G. D. (2013). *Confronting Gangs: Crime and Community* (3 ed.).

Pyrooz, D. C., Sweeten, G., & Piquero, A. R. (2013). Continuity and Change in Gang Membership and Gang Embeddedness. *Journal of Research in Crime and Delinquency*, *50*(3), 239-271.

Ratcliffe, J. H., Perenzin, A., & Sorg, E. T. (2017). Operation Thumbs Down: A quasi-experimental evaluation of an FBI gang takedown in South Central, Los Angeles. *Policing: An International Journal of Police Strategies & Management*, *40*(2), 442-458.

Reiss, A. J. J. (1988). Co-offending and Criminal Careers. In N. Morris & M. Tonry (Eds.), *Crime and Justice Vol. 10* (pp. 121-160). University of Chicago Press.

Repetto, T. A. (1976). Crime Prevention and the Displacement Phenomenon. *Crime and Delinquency*, *22*(2), 166-177.

Ripley, R. M., Snijders, T. A. B., Boda, Z., Voros, A., & Preciado, P. (2018). *Manual for RSiena*. In University of Oxford: Department of Statistics Nuffield College University of Groningen: Department of Sociology

Rogers, E. M. (2002). Diffusion of Preventative Innovations. *Addictive Behaviors*, *27*, 989-993.

Rogers, E. M. (2003). *Diffusion of Innovations*. The Free Press.

Roman, C. G., Cahill, M., Coggeshall, M., Lagerson, E., & Courtney, S. (2005). *An Examination of Spatial Displacement Associated with Crime Control Initiatives and the Redevelopment of Public Housing*. Washington, D.C.: Justice Policy Center

Rose, D. R., & Clear, T. R. (1998). Incarceration, Social Capital and Community Life. *Criminology*, *36*, 441-479.

Sampson, R. J. (2010). Gold Standard Myths: Observations on the Experimental Turn in Quantitative Criminology. *Journal of Quantitative Criminology*, *26*, 489-500.

Sampson, R. J., & Wilson, W. J. (1995). Toward a Theory of Race, Crime and Urban Inequality. In J. Hagan & R. D. Peterson (Eds.), *Crime and Inequality* (pp. 37-56). Stanford University Press.

Sarnecki, J. (2001). *Delinquent Networks: Youth Co-Offending in Stockholm*. University Press.

Schaefer, D. (2017). Social Networks and Health Workshop: Siena Models.

Scott, J. (2001). *Social Network Analysis: A Handbook* (Second ed.). Sage.

Shalizi, C. R., & Thomas, A. C. (2011). Homophily and Contagion Are Generically Confounded in Observational Social Network Studies. *Social Methods Res.*, *40*(2), 211-239. https://doi.org/10.1177/0049124111404820

Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot Spots of Predatory Crime: Routine Activities and the Criminology of Place. *Criminology*, *27*(1), 27-56.

Sherman, L. W., Gottfredson, D., MacKenzie, D., Eck, J., Reuter, P., & Bushway, S. (1997). *Preventing Crime: What Works, What Doesn't, What's Promising*. Washington, D.C.: Department of Justice

Sherman, L. W., & Weisburd, D. (1995). General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial. *Justice Quarterly*, *12*(4), 625-648.

Short, J. F., & Strodtbeck, F. L. (1974). *Group Process and Gang Delinquency*. University of Chicago Press.

Shumante, M., Pilny, A., Atouba, Y. C., Pena-y-Lillo, M., Cooper, K. R., Sahagun, A., & Yang, S. (2016). A Taxonomy of Communication Networks. *Communication Yearbook*, *37*, 95-123.

Sierra-Arevalo, M., & Papachristos, A. V. (2015). Social Network Analysis and Gangs. In S. Decker & D. C. Pyrooz (Eds.), *The Handbook of Gangs*. Wiley.

Silberman, M. (1976). Toward a theory of criminal deterrence. *American Sociological Review*, *41*, 442-461.

Smangs, M. (2010). Delinquency, Social Skills and the Structure of Peer Relations: Assessing Criminological Theories by Social Network Theory. *Social Forces*, *2*, 609-632.

Smith-Hefner, N. J. (1999). *Khmer American: Identity and Moral Education in a Diasporic Community*. University of California Press.
Snijders, T. A. B. (2017). Stochastic Actor-Oriented Models for Network Dynamics. In S. Fienberg, N. Reid, & S. Stigler (Eds.), *Annual Review of Statistics and Its Application* (Vol. 4, pp. 343-363).
Snijders, T. A. B., Steglich, C. E. G., & Schweinberger, M. (2007). Modeling the Co-evolution of Networks and Behavior. In H. O. van Montfort & A. Satorra (Eds.), *Longitudinal Models in the Behavioral and Related Sciences* (pp. 41-71). Erlbaum.
Snijders, T. A. B., van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to Stochastic Actor-Based models for Network Dynamics. *Social Networks*, *32*, 44-60.
Sorg, E. T., Haberman, C. P., Ratcliffe, J. H., & Groff, E. R. (2012). Foot Patrol in violent crime hot spots: The longitudinal impact of deterrence and post treatment effects of displacement. *Criminology*, *51*, 65-102.
Spergel, I. A., & ebrary, I. (1995). *The youth gang problem : a community approach*. Oxford University Press.
Spergel, I. A., Wa, K. M., Choi, S. E., Grossman, S., Ayad, J., Spergel, A., & Barrios, E. M. (2003). *Evaluation of the Gang Violence Reduction Project in Little Village: Final Report Summary*. Chicago: University of Chicago
Stadtfeld, C., Snijders, T. A. B., Steglich, C., & van Duijn, M. (2018). Statistical Power in Longitudinal Network Studies. *Sociological Methods and Research*, 1-18.
Stafford, M. C., & Warr, M. (1993). A Reconceptualization of General and Specific Deterrence. *Journal of Research in Crime and Delinquency*, *30*(2), 123-135.
Steglich, C., Snijders, T. A. B., & Pearson, M. (2010). Dynamic Networks and Behavior: Separating Selection from Influence. *Sociological Methodology*, *40*.
Tang, S. S. (2010). Diasporic Cultural Citizenship: Negotiate and Create Places and Identities in Their Refugee Migration and Deportation Experiences. *Trotter Review*, *19*(1).
Thomas, K. J., Loughran, T. A., & Piquero, A. R. (2013). Do Individual Characteristics Explain Variation in Sanction Risk Updating Among Serious Juvenile Offenders? Advancing the Logic of Differential Deterrence. *Law and Human Behavior*, *37*(1), 10-21.
Tita, G., & Ridgeway, G. (2007). The Impact of Gang Formation on Local Patterns of Crime. *Journal of Research in Crime and Delinquency*, *44*(2), 208-237.
Tittle, C. R., & Rowe, A. R. (1973). Moral Appeal, Sanction Threat, and Deviance: An Experimental Test. *Social Problems*, *20*, 488-498.
United States District Attorney, D. o. M. (2010). *Forty-Eight Alleged Lynn Gang Members and Associates Charged in Sweeping Federal and State Firearm and Gang Trafficking Investigation: Authorities Seize Guns, Drugs, Money*
Valente, T. (1995). Network Models of the Diffusion of Innovations. *Computational and Mathematical Organization Theory*, *2*(2), 163-164.
Valente, T. W. (1999). Social Network Thresholds in the Diffusion of Innovations. *Social Networks*, *18*, 69-89.
Valente, T. W. (2012). Network Interventions. *Science*, *337*.
Valente, T. W., & Davis, R. L. (1999). Accelerating the Diffusion of Innovation Using Opinion Leaders. *American Academy of Political and Social Science*, *566*, 55-67.
Wacquant, L. (2009). The Body, the Ghetto and the Penal State. *Qualitative Sociology*, *32*, 101-129.
Wagner, A. (May 29th, 2019). *FBI special agent recognized for record takedown of MS-13 gang.* Government Matters. Retrieved January 30 from https://govmatters.tv/fbi-special-agent-recognized-for-record-takedown-of-ms-13-gang/#//

Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Application*. Cambridge University Press.

Weisburd, D. (Ed.). (1993). *Design sensitivity in criminal justice experiments.* (Vol. 17). University of Chicago Press.

Weisburd, D. (2008). Place-Based Policing. *Ideas in American Policing*, *9*, 1-16.

Weisburd, D. (2010). Justifying the use of non-experimental methods and disqualifying the use of randomized controlled trials: challenging folklore in evaluation research in crime and justice. *Journal of Experimental Criminology*, *6*(2), 209–227.

Weisburd, D., & Eck, J. E. (2004). What Can Police Do to Reduce Crime, Disorder and Fear? *The ANNALS of the American Academy of Political and Social Sciences*, *593*.

Weisburd, D., Lum, C. M., & Petrosino, A. (2001a). Does Research Design Affect Study Outcome in Criminal Justice? *The ANNALS of the American Academy of Political and Social Science*, *578*.

Weisburd, D., Lum, C. M., & Petrosino, A. (2001b). Does research design affect study outcomes in criminal justice? *The Annals of the American Academy of Political and Social Science*, *578*(1), 50-70.

Weisburd, D., & Majmundar, M. K. (2018). *Proactive Policing: Effects on Crime and Community*. The National Academies Press.

Weisburd, D., Wyckoff, L. A., Ready, J., Eck, J., Hinkle, J. C., & Gajewski, F. (2006). Does Crime Just Move Around the Corner? A Controlled Study of Spatial Displacement and Diffusion of Crime Control Benefits. *Criminology*, *44*(3).

Weisel, D. L. (2002). *The Evolution of Street Gangs: An Examination of Form and Variation.* National Institute of Justice.

Welsh, B. C., Sullivan, C. J., & Olds, D. L. (2010). When early crime prevention goes to scale: A new look at the evidence. *Prevention Science*, *11*, 115-125.

Wertheimer, M., & Riezler, K. (1984). *Gestalt Theory* Social Research,

Western, B., & Muller, C. (2013). Mass Incarceration, Macrosociology, and the Poor. *The ANNALS of the American Academy of Political and Social Science*, *647*.

Williams, K. R., Gibbs, J. P., & Erickson, M. L. (1980). Public Knowledge of Statutory Penalties: The Extent and Basis of Accurate Perception. *Pacific Sociological Association*, *23*(1), 105-128.

Wilson, J. Q., & Herrnstein, R. J. (1985). *Crime and Human Nature*. Simon and Shuster.

Wilson, T., Paternoster, R., & Loughran, T. (2017). Direct and Indirect Experiential Effects in an Updating Model of Deterrence: A Research Note. *Journal of Research in Crime and Delinquency*, *54*(1), 63-77.

Wilson, T., Paternoster, R., & Loughran, T. A. (2017). Direct and indirect experiential effects in an updating model of deterrence: a research note. *Journal of Research Crime and Delinquency*, *54*, 63-77.

Wood, J., & Alleyne, E. (2010). Street gang theory and research: Where are we now and where do we go from here? *Aggression and Violent Behavior*, *15*, 100-111.

Woods, J. B. (2012). Systemic Racial Bias and RICO's Application to Criminal Street and Prison Gangs. *Michigan Journal of Race and Law*, *17*.

Zimring, F., & Hawkins, G. (1968). Deterrence and Marginal Groups. *Journal of Research in Crime and Delinquency*, *5*(2), 100-114.